The effect of partner and household characteristics on the continued employment of coupled older women in England

A thesis submitted to The University of Manchester for the degree of Doctor of Philosophy in the Faculty of Humanities

2016

Jennifer Prattley

School of Social Sciences
# Contents

List of Figures ......................................................................................... 8

List of Tables .......................................................................................... 11

Abstract .................................................................................................... 15

Declaration ............................................................................................... 16

Copyright Statement ................................................................................ 17

Acknowledgements .................................................................................. 18

1 Literature review .................................................................................. 19
   1.1 Introduction .................................................................................... 19

   1.2 Theoretical perspectives on the retirement process ......................... 21
      1.2.1 Productive ageing .................................................................... 22
      1.2.2 The social divisions of welfare .................................................. 23
      1.2.3 Rational choice theory ............................................................... 24
      1.2.4 The life course approach ............................................................ 24
      1.2.5 The Third Age framework ........................................................ 25
      1.2.6 Decision theory ........................................................................ 27
      1.2.7 A multilevel perspective ............................................................ 28

   1.3 Conceptualizing and measuring retirement ...................................... 29

   1.4 Long term trends in later life employment ....................................... 30
      1.4.1 Trends in employment, inactivity and unemployment rates .......... 31
      1.4.2 The influence of period and cohort effects .................................. 33
1.5 The institutional context ................................................. 34
  1.5.1 Labour market structures ........................................ 34
  1.5.2 Social security regimes ........................................... 35
1.6 Individual and household level predictors of later life employment .... 37
  1.6.1 Economic feasibility of retirement ............................... 38
  1.6.2 Employment history and working patterns ..................... 46
  1.6.3 Non voluntary factors ............................................ 48
  1.6.4 Attitudinal and dispositional effects ............................ 50
1.7 The domestic context of single older women .......................... 51
1.8 Research questions and hypotheses .................................. 53

2 Methods .............................................................................. 56
  2.1 Introduction ................................................................. 56
  2.2 Description of data ....................................................... 57
    2.2.1 The selected ELSA sample ...................................... 57
    2.2.2 The selected ELSA questions .................................... 61
  2.3 Modelling approach and strategy ...................................... 70
    2.3.1 Modelling the incidence and timing of women’s and male partners’ employment exit ........................................ 71
    2.3.2 Modelling the destination state and subsequent pathway .......................................................... 74
  2.4 Measuring time and employment events ............................... 76
    2.4.1 Structure of the time axis ....................................... 76
    2.4.2 Defining key employment events ............................... 78
  2.5 Missing data ................................................................. 79
    2.5.1 Delayed entry ....................................................... 79
    2.5.2 Censorship ........................................................... 80
    2.5.3 Missingness within the observation window .......... 80
  2.6 Characteristics of the sample ........................................... 85
    2.6.1 Observed sample transition rates by age ...................... 85
    2.6.2 Women’s and male partners’ individual level attributes .... 86
    2.6.3 Household measures .............................................. 91
3 Coupled women’s transitions from employment

3.1 Introduction

3.2 Method

3.3 The baseline hazard function

3.4 Individual level predictors

3.4.1 Control factors

3.4.2 Key interest predictors: proportional effects

3.4.3 Key interest predictors: non proportional effects

3.4.4 The effects of individual level attributes - summary

3.5 Household level predictors

3.5.1 Tenure

3.5.2 Household pension wealth

3.5.3 Household non pension wealth

3.5.4 The influence of household factors - summary

3.6 Male partner characteristics

3.6.1 Partner’s employment status

3.6.2 Partner’s limiting health

3.6.3 Have partner covariates modified individual effects?

3.7 Diagnostics

3.7.1 Goodness of fit

3.7.2 Influential cases

3.7.3 Summary

3.8 Random effects model

3.8.1 Rationale for fitting a random effect model

3.8.2 Results

3.9 Interpretation and contribution of results

3.9.1 Identifying significant predictors of older women’s employment transitions

3.9.2 Measuring and ranking the impact of predictors
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.9.3 Constructing longitudinal risk profiles</td>
<td>150</td>
</tr>
<tr>
<td>3.10 Summary</td>
<td>153</td>
</tr>
<tr>
<td>4 Determinants of women’s voluntary and involuntary transitions</td>
<td>155</td>
</tr>
<tr>
<td>4.1 Introduction</td>
<td>155</td>
</tr>
<tr>
<td>4.2 Descriptives of alternative exit groups</td>
<td>156</td>
</tr>
<tr>
<td>4.2.1 The effect of women’s individual characteristics</td>
<td>157</td>
</tr>
<tr>
<td>4.2.2 Sample transition rates according to household characteristics</td>
<td>164</td>
</tr>
<tr>
<td>4.2.3 Observed transition type according to partner characteristics</td>
<td>167</td>
</tr>
<tr>
<td>4.3 Method</td>
<td>170</td>
</tr>
<tr>
<td>4.4 Results</td>
<td>171</td>
</tr>
<tr>
<td>4.4.1 Age and control factors</td>
<td>171</td>
</tr>
<tr>
<td>4.4.2 Key individual factors: health, caring and working hours</td>
<td>172</td>
</tr>
<tr>
<td>4.4.3 Household factors: wealth and tenure</td>
<td>172</td>
</tr>
<tr>
<td>4.4.4 Partner factors</td>
<td>176</td>
</tr>
<tr>
<td>4.5 Summary</td>
<td>178</td>
</tr>
<tr>
<td>4.5.1 Predictors of the timing of older women’s employment exit</td>
<td>178</td>
</tr>
<tr>
<td>4.5.2 Predictors of voluntary and involuntary pathways</td>
<td>179</td>
</tr>
<tr>
<td>4.5.3 The interaction between the domestic context and older women’s employment transitions and pathways</td>
<td>180</td>
</tr>
<tr>
<td>5 Partner employment transitions</td>
<td>182</td>
</tr>
<tr>
<td>5.1 Introduction</td>
<td>182</td>
</tr>
<tr>
<td>5.2 Descriptive analysis of male partner data</td>
<td>184</td>
</tr>
<tr>
<td>5.2.1 Observed transition rates over time</td>
<td>184</td>
</tr>
<tr>
<td>5.2.2 Male partner individual characteristics</td>
<td>185</td>
</tr>
<tr>
<td>5.2.3 Household factors</td>
<td>188</td>
</tr>
<tr>
<td>5.2.4 Female partner factors</td>
<td>189</td>
</tr>
<tr>
<td>5.3 Modelling approach and strategy</td>
<td>191</td>
</tr>
<tr>
<td>5.3.1 Covariate measures</td>
<td>192</td>
</tr>
<tr>
<td>5.4 Results</td>
<td>193</td>
</tr>
</tbody>
</table>
# List of Figures

1.1 Long term trends in employment, unemployment and inactivity rates . . . . 32
1.2 Proportion of pensioners on different percentages of basic state pension . . 39
1.3 Family pension wealth and total wealth holdings by decile group . . . . . 41

2.1 Sample selection process. ....................................................... 59
2.2 Age distribution at baseline for women and male partners .................. 77
2.3 Missingness within covariate measures .................................... 83
2.4 Income distribution at baseline for women and male partners ................ 89
2.5 Confidence interval for estimated pension wealth coefficient for 70th to 99th pension wealth percentile groups ........................................... 95

3.1 Observed and predicted transition rates for women’s employment exit according to limiting health status .......................................................... 108
3.2 Observed and predicted transition rates for women’s employment exit according to onset of limiting health ......................................................... 111
3.3 Observed and predicted transition rates for women’s employment exit according to self rated health status ......................................................... 113
3.4 Observed and predicted transition rates for women’s employment exit according to caring responsibilities .......................................................... 115
3.5 Predicted proportional effects and observed women’s employment transition rates for part time and full time workers .......................................... 116
3.6 Observed and predicted women’s employment transition rates for part time and full time workers with age interaction ........................................ 121
3.7 Predicted women’s employment transition rates according to housing status 125
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.8</td>
<td>Observed and predicted women’s employment transition rates for partner’s employment status</td>
</tr>
<tr>
<td>3.9</td>
<td>Deviance residual plots for event history model of women’s transition from employment</td>
</tr>
<tr>
<td>3.10</td>
<td>Leverage plots from final logistic regression model for predicting women’s employment transitions</td>
</tr>
<tr>
<td>3.11</td>
<td>DFBetas against predicted conditional probability of women’s transition for income covariates</td>
</tr>
<tr>
<td>3.12</td>
<td>Sample selection effect</td>
</tr>
<tr>
<td>3.13</td>
<td>Significant predictor risk trajectories for women’s employment transitions</td>
</tr>
<tr>
<td>3.14</td>
<td>Predicted health trajectories for women’s employment transitions</td>
</tr>
<tr>
<td>4.1</td>
<td>Sequence plots for transitioned women by transition type</td>
</tr>
<tr>
<td>4.2</td>
<td>Observed proportion of involuntary and voluntary women’s employment transitions by age</td>
</tr>
<tr>
<td>4.3</td>
<td>Women’s income distribution by transition type</td>
</tr>
<tr>
<td>4.4</td>
<td>Distribution of male partner’s age by transition type</td>
</tr>
<tr>
<td>4.5</td>
<td>Distribution of male partner’s income by type of transition</td>
</tr>
<tr>
<td>4.6</td>
<td>Older women’s pathways to retirement</td>
</tr>
<tr>
<td>5.1</td>
<td>Proportion of observed transitions by gender and woman’s age</td>
</tr>
<tr>
<td>5.2</td>
<td>Limiting health trajectories for women and male partners</td>
</tr>
<tr>
<td>5.3</td>
<td>Part time working trajectories for women and male partners</td>
</tr>
<tr>
<td>5.4</td>
<td>Estimated transition probability by pension wealth quintile for male partners</td>
</tr>
<tr>
<td>6.1</td>
<td>Proportion of sample of working women observed by age, prior to removal of cases with missing data</td>
</tr>
<tr>
<td>6.2</td>
<td>Women’s observation patterns according to age</td>
</tr>
<tr>
<td>6.3</td>
<td>Women’s employment transition rate by age in imputed and observed outcomes only datasets</td>
</tr>
<tr>
<td>6.4</td>
<td>Distribution of women by age at each observation point</td>
</tr>
<tr>
<td>7.1</td>
<td>Older women’s pathways to retirement</td>
</tr>
</tbody>
</table>
7.2 Risk trajectories for significant predictors of women’s labour market exit . 252
7.3 Older women’s pathways to retirement with increase in state pension age . 263
List of Tables

1.1 Annual pension payments for pensioner couples in 2008/09 (£) .......................... 39
1.2 Distribution of total pension wealth for families aged 50 - state pension age,
by employment status (£000s) .............................................................. 42
1.3 Absolute life expectancy at age 50 by gender, 2005 - 2011 ................................. 46
1.4 Annual pension payments for single female pensioners in 2008/09 (£) ............... 51

2.1 Distribution of removed records among women with missing individual, house-
hold and partner measurements .............................................................. 84
2.2 Sample transition rate for each year of women’s age ....................................... 86
2.3 Observed statistics for women’s and male partner samples at time of first
ELSA response ....................................................................................... 87
2.4 Observed household level sample statistics for women’s and male partner
samples at time of first ELSA response .................................................... 92
2.5 Minimum and maximum pension wealth values for quintiles at age 55 (£000s) 93
2.6 Number of sampled women, records and transitions above a range of pension
wealth percentiles .................................................................................... 94
2.7 Assignment of households to non pension and pension wealth quintile groups
at baseline ............................................................................................... 97

3.1 Sample transition rate for each year of women’s age ....................................... 102
3.2 Parameter estimates for the baseline hazard function from discrete time event
history models for the conditional probability of women’s transition from
employment ................................................................................................. 103
3.3 Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with proportional individual level covariates .......................................................... 106
3.4 Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with non proportional individual level covariates .......................................................... 119
3.5 Predicted conditional probability of women’s transition by working hours (%) 122
3.6 Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with household level covariates .......................................................... 123
3.7 Observed women’s employment transition rates according to pension and non pension wealth quintiles .......................................................... 127
3.8 Risk differential for women’s employment transition estimated by individual and household level models .......................................................... 128
3.9 Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with partner level covariates .......................................................... 129
3.10 Risk differential for women’s employment transitions estimated by household and partner models for individual level covariates ................. 133
3.11 Parameter estimates from single level discrete time event history model and random intercept model, for the conditional probability of women’s transition from employment .......................................................... 145
3.12 Comparison of estimated effects from single level and random intercept event history models for women’s transition .......................................................... 146
4.1 Number and percentage of women transitioned by type of exit and age .... 159
4.2 Distribution of women’s voluntary and involuntary transitions for individual level socio demographic variables .......................................................... 162
4.3 Distribution of voluntary and involuntary women’s transitions for key individual level covariates .......................................................... 162
5.9 Parameter estimates from discrete time event history models for the conditional probability of male partner transitions from employment, with female partner covariates .............................................................. 201
5.10 Estimated percentage increase in women’s and male partners’ estimated conditional probability of transition, for selected covariates ......................... 204

6.1 Transition rate for each age group with and without imputed outcomes (%) . 214
6.2 Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, for women observed from ages 50 - 52, using interval baseline hazard function with individual level covariates ......................................................... 223
6.3 Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, for women observed from ages 50 - 52, using interval baseline hazard function with household level covariates ......................................................... 226
6.4 Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, for women observed from ages 50 - 52, using interval baseline hazard function with male partner level covariates ......................................................... 227
6.5 Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, using time on study baseline hazard function with individual level covariates .............. 229
6.6 Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, using time on study baseline hazard function with household level covariates ............ 231
6.7 Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, using time on study baseline hazard function with partner level covariates .............. 232
6.8 Significant coefficients and standard errors from event history models for predicting women’s transition under different sample selection criteria and time metrics ................................................................. 235
Abstract

For the degree of Doctor of Philosophy

The University of Manchester

Jennifer Prattley

23 July 2016

The effect of partner and household characteristics on the continued employment of coupled older women in England

The economic wellbeing, physical and mental health of the ageing population in the United Kingdom is associated with continued participation in the labour force. Encouraging later life employment is therefore a key policy issue. Research into older person’s employment trajectories is concentrated on male working patterns, and often takes an individualistic approach that does not account for the domestic context. Previous research on women’s labour force participation has been informed by small scale qualitative studies that do consider the household domain but these findings cannot be generalized to the wider population. This research investigates the factors associated with the continued employment of women aged 50 to 59 using data from the English Longitudinal Study of Ageing (ELSA). Transition rates out of employment between 2001 and 2011 are modelled using multilevel discrete time event history specifications that permit the inclusion of time varying covariates. Retirement is characterized as an ageing process which allows the impact of predictors on transition rates to be assessed and measured as women approach state pension age. Alternative time structures are considered, with parameter estimates from an age baseline model compared with those from a time on study specification. Results illustrate the sensitivity of parameter estimates in discrete time event history models to the measurement of time, and emphasise the importance of adopting a time metric that is commensurate with the theoretical representation of retirement as a dynamic ageing process.

The domestic context is realised as sampled women and their male partners are positioned within a household structure, and asymmetric effects of predictors on the transition rate of each gender are considered. Own poor health, caring responsibilities and a retired or inactive spouse accelerate labour market exit for women whilst high levels of accrued pension wealth predict earlier transitions for their male partners. The age of employment exit for females is independent of pension wealth, but pension resources do predict the retirement pathway taken following any transition that does occur. Women residing in the wealthiest households are more likely to report as voluntary retired prior to state pension age whilst those in the poorest of couples are at higher risk of following an involuntary pathway into an alternative inactive state. These findings emphasise the importance of conducting research into later life employment trajectories on a household, rather than individual, basis.
Declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.
Copyright statement

i. The author of this thesis (including any appendices and/or schedules to this thesis) owns certain copyright or related rights in it (the “Copyright”) and s/he has given The University of Manchester certain rights to use such Copyright, including for administrative purposes.

ii. Copies of this thesis, either in full or in extracts and whether in hard or electronic copy, may be made only in accordance with the Copyright, Designs and Patents Act 1988 (as amended) and regulations issued under it or, where appropriate, in accordance with licensing agreements which the University has from time to time. This page must form part of any such copies made.

iii. The ownership of certain Copyright, patents, designs, trade marks and other intellectual property (the “Intellectual Property”) and any reproductions of copyright works in the thesis, for example graphs and tables (“Reproductions”), which may be described in this thesis, may not be owned by the author and may be owned by third parties. Such Intellectual Property and Reproductions cannot and must not be made available for use without the prior written permission of the owner(s) of the relevant Intellectual Property and/or Reproductions.

iv. Further information on the conditions under which disclosure, publication and commercialisation of this thesis, the Copyright and any Intellectual Property and/or Reproductions described in it may take place is available in the University IP Policy (see http://documents.manchester.ac.uk/DocuInfo.aspx?DocID=487), in any relevant Thesis restriction declarations deposited in the University Library, The University Library’s regulations (see http://www.manchester.ac.uk/library/aboutus/regulations) and in The University’s policy on presentation of Theses
Acknowledgements

Sincere thanks must go to my supervisory team; firstly, to Professor Tarani Chandola for seeing the potential, and letting me find my own way to all these words so nicely organised into chapters. Thanks to Dr Johan Koskinen for having such insight and sage advice, and to Dr Bram Vanhoutte for those important words of encouragement and reassurance. It has been a privilege to learn from, and be guided by, the three of you.

Thank you to my fellow students and staff from the Cathie Marsh Institute for Social Research for the many thought provoking conversations and friendships made along the way. Particular thanks to Pip Walker for helping me navigate a way through, and to Dr Nick Shrayne for his support in reaching the end. Also much gratitude goes to my good friends elsewhere who, whether near or far, have been a valued source of the humour, wisdom and acceptance necessary for getting to this point. The Economic and Social Research Council provided generous financial support.
Chapter 1

Literature review

1.1 Introduction

The United Kingdom government and society are ‘woefully underprepared’ for the implications of a rapidly ageing population, concluded the House of Lords Select Committee on Public Service and Demographic Change in March 2013 (House of Lords, 2013, p. 7). One recommended course of action by the committee, published in their ‘Ready for Ageing?’ report, is to encourage the continued employment of older workers as financial support from state sources is likely to be insufficient to sustain a good standard of living in retirement. Benefits outlined in the report of individuals choosing to work for longer include improved physical and mental health and wellbeing, with resulting healthcare savings to the wider society.

Explicit in the findings of the Select Committee is that ‘the choice to continue in work is one that must remain entirely with the individual’ with the role of employers and the government to provide incentives, and remove disincentives, for continued work (House of Lords 2013, p. 32). However the degree of choice that an individual has in the retirement decision is a function of not only their own personal characteristics such as income, pension provision and health, but also those of their spouse or partner (Szinovacz and Deviney, 2000; Loretto and Vickerstaff, 2013). The value of combined household financial assets, expected household retirement income, and consequences of the partner’s poor health might also be relevant to the decision to remain in work.

The importance of the household context in the retirement decision is not widely studied
in the United Kingdom. Rather, research into retirement patterns has been largely restricted to that of men, and an individualistic approach is often taken. With the proportion of women aged 50 and over participating in the labour force increasing significantly over recent decades the limitations of such choices are evident. The current understanding of factors that impact on men’s retirement decisions may need to be re-examined to determine any effect of working wives, and there is limited appreciation of the reasons why older women might choose to remain in the labour market. The impact of the family is stronger on female employment patterns throughout the lifecourse (Everingham et al., 2007), and this can lead to women taking non standard pathways out of work that are characterized by the domestic context (Loretto and Vickerstaff, 2013). It cannot be assumed, therefore, that factors known to influence men’s retirement trajectories will impact equally on older women’s employment patterns.

Household level analysis that does consider women’s roles in the retirement decision making process have been conducted by German (Blau and Riphahn, 1999; Drobnič, 2002), Danish (Bingley and Lanot, 2007) and American researchers (Szinovacz and Deviney, 2000); however older persons in England live in different welfare and labour market contexts and these international findings, whilst informative, will not necessarily hold for English households.

The state of the economy is one of the most important macrolevel contextual factors that impacts on older person’s attachment to the labour market (Szinovacz, 2012). The UK economy entered a recessionary state in early 2008, and as evidenced from the economic downturns of the 1980s and early 1990s employment patterns of the older population differ between times of economic growth and periods of recession (Gregg and Wadsworth, 2010). What is also known, however, from examination of previous downturns, is that the labour market behaviour of older workers changes between recessionary eras (Disney et al., 2011).

In the 1980s and 1990s downturns, persons aged 50 and over were employed in industries that suffered a disproportionate amount of job losses and were encouraged to retire on health grounds or to leave in order to create jobs for their younger counterparts. This has not been the case in the most recent recession. Despite gross domestic product declining further, and faster, than in earlier downturns (Gregg and Wadsworth, 2010) the employment rate for women aged 50 to 64 has increased, and that for men has decreased by much less than that of their younger counterparts. The global economic crisis had negative consequences for
financial markets and pension funds in the UK (Lagoutte and Reimat, 2013), and any fall in expected retirement income may have influenced older men’s and women’s retirement decisions.

With existing research into retirement patterns in the United Kingdom concentrating on men, disregarding the household context, and in view of the changing economic situation between 2008 and 2011, this research examines the dependency of coupled older women’s employment exit on household and spousal characteristics. The theoretical framework for this work is established in the next section and following that, in Section 1.3, measures of retirement are discussed. Section 1.4 contains empirical evidence relating to the labour market participation of older persons. The labour market structure and social security regime of the United Kingdom is explained in Section 1.5 and household and individual level factors that may impact on older persons’ employment are detailed in Section 1.6. Section 1.7 compares the domestic context of coupled and single older women. The research questions and hypotheses of this thesis are stated in Section 1.8.

1.2 Theoretical perspectives on the retirement process

The retirement process is a complex one, influenced by an individual’s previous and current experiences that take place within dynamic social structures (Szinovacz, 2003; Madero-Cabib et al., 2016). Phillipson (2004, p. 189) describes how, despite a ‘substantial literature’ of empirical studies into this process, related theoretical frameworks are ‘relatively under-developed’. Despite this the frameworks discussed in his review - productive ageing, the social division of welfare structure and the life course approach - are useful for identifying the components needed for an accurate theoretical representation of retirement. In this section these three perspectives are discussed alongside aspects of rational choice theory, the Third Age approach and decision theory. Current research surrounding women’s retirement is integrated where appropriate.
1.2.1 Productive ageing

The productive ageing framework is constructed from the viewpoint that older persons are under represented as contributors to society (Bass and Caro, 2001). However there are multiple and evolving definitions for the concept, with debate centred on the activities that can be regarded as ‘productive’. Morrow-Howell et al. (2001) assert that the idea is often narrowed to participation in paid employment with insufficient attention given to other activities performed outside of the labour market. This can devalue older women’s contributions to wider society as they tend to devote more time to unpaid domestic work and care. Bass (2011, p. 179) does find a common argument amongst scholars that society should offer older individuals opportunities for ‘meaningful engagement’. This engagement can include paid employment, unpaid volunteer work and care provided to family or other persons in need.

The focus of this thesis, however, is primarily on women’s participation in market work. Employment rates for older persons in the United Kingdom show an increasing proportion of this age group are in paid work, but there are gender differences within this population. Between 2001 and 2011 the employment rate for men aged 50 to state pension age has risen by 0.1 percentage points, whilst that for women aged 50 to state pension age has increased by 7.4 percentage points (Eurostat, 2012). This suggests a shift within the older female population towards productivity in the form of paid work - this is a notable trend that has not been widely researched and motivates our research. A more detailed presentation of labour market statistics for this age group is given later, in Section 1.4. Morrow-Howell et al. (2001) claim that women tend to move between the different forms of productive engagement more often than men, and the intention in this thesis is to analyse their market employment and consider the impact that other forms of activity, such as the provision of care, have on their continued engagement in the workforce.

Bass (2011) considers the productive ageing framework and it’s relevance to current cohorts of retirees. He concludes that a productively ageing society has not been fully realised and attributes this to the prevailing economic circumstances. A shift towards defined contribution pension schemes, as well as the recent recession, has increased uncertainty in pension income and this limits the degree of choice an older person has over their participation in productive activities, however defined. It could be argued, however, that women have histor-
ically been constrained in their ability to productively engage as they tend to take responsi-

bility for family duties and caring needs; these may arise due to involuntary circumstances
involving illness and poor health and impact on their opportunities to pursue other interests.
Any further constraints caused by recent insecurity in the financial markets, therefore, may
be considered as exacerbating these limitations already operating on older women.

1.2.2 The social divisions of welfare

The social divisions of welfare framework presented by Mann (2001) details the sources
of support available to retirees and links them to differences in retirement timing, income
and choices. Four types of welfare are identified. Public welfare includes the state pension,
unemployment benefits and disability insurance, whilst occupational pensions offered by
private and public sector employers are a second type. Personal private pensions held by
financial institutions and informal welfare drawn from within the family are the remaining
two. Mann (2001, p. 39) examines the recipients, value and reliability of each welfare
type and concludes that ‘every aspect’ of the social divisions approach is gendered. Older
women tend to provide a disproportionate amount of informal welfare in the form of care
and domestic work and this can lead to their exclusion from the occupational, private and
public forms of support. They are, consequently, more likely to depend on their spouse for
financial wellbeing and are at greater risk of poverty in old age.

Mann (2001) differentiates between the concept of retirement and that of labour force
exit, by referring to the occupational and private pension welfare sources. Future retirees, he
claims, may be those who have made sufficient contributions to a reliable pension fund and
this population may be distinct from those who leave the workforce for involuntary reasons
such as poor health, redundancy or age discrimination. This assertion is commensurate with
the affluence/leisure hypothesis which states that older individuals will work in times of
financial need but retire otherwise, with individuals assumed to base the retirement decision
on the sufficiency of financial resources (Bass and Caro, 2001). Rational choice theory is
one mechanism by which individuals may evaluate the adequacy of their retirement funds
and is described in the next section.
1.2.3 Rational choice theory

Rational choice theory has guided much retirement research (Wang and Shultz, 2010, p. 184) and states that individuals will retire if accumulated resources are sufficient to meet future consumption needs given anticipated economic conditions (Hatcher, 2003). An assumption underlying rational choice theory is that retirees have ‘comprehensive and accurate information about themselves and the situation’ when making their decision (Wang and Shultz, 2010, p. 186). However research by Crawford and Tetlow (2012b, p. 1, 2) illustrates the limitation of this. Using data from the English Longitudinal Study of Ageing these authors found that 59% of individuals aged between 50 and 64 and not yet retired had never thought about the number of years of retirement they would need to finance; and amongst persons with private pension resources, almost one third were not able to identify a range within which their future pension income would fall. Hence in reality many older persons do not have the complete or accurate information assumed in perfect rational choice theory. A bounded rationality approach might be more appropriate as this recognises limitations in available information - however Wang and Shultz (2010) report that there is no existing theoretical framework that incorporates the uncertainty inherent in the retirement decision making process.

Persons for whom labour market exit is involuntary further illustrate the limitations of rational decision making theory as applied to retirement. These employees leave work due to poor health or forced job loss, for example, and enter unemployment or an alternative inactive state. Loretto and Vickerstaff (2013) identify couples where both partners are in one of these positions and are reliant on unemployment or disability benefits for support. In such cases a passive approach to retirement is taken with its beginning defined by reaching the official state pension age rather than any employment transition. A theory of retirement based on either perfect or bounded rationality will not apply in such circumstances where individuals have little control over their labour market participation (Wang and Shultz, 2010).

1.2.4 The life course approach

In the life course approach retirement is depicted as the outcome of a series of actions that take place within interconnecting and mutually influential domains. The family and work
contexts can be regarded as two such overlapping spheres (Szinovacz et al., 2001; Madero-Cabib et al., 2016). The ‘linked lives’ principle recognises that experiences of the partner, child or other family member impact on an older woman’s employment choices and the ‘contextual embeddedness’ component allows for heterogeneity across individual and household circumstances. In the context of retirement trajectories, for example, poor health of a spouse may accelerate a woman’s exit from the workforce if she takes responsibility for providing care. The likelihood of this happening, however, may be contingent on the financial resources of the couple with the woman’s continued employment more likely if her income is needed to ensure the couple’s economic wellbeing. As illustrated with this example, the life course approach allows for actions and experiences that take place within a constrained environment where individuals have limited or no choice or control over events.

Life course theory affords a long term view of the retirement experience with the principle of cumulative advantage and disadvantage. This emphasises continuity across the life course, with advantages in health, education and material resources likely to persist into later life (Moen, 2011); it therefore provides a framework that can account for any association between women’s earlier employment experiences and their standard of living when older. Women have a higher incidence of poverty in later life than their male counterparts (Mann, 2001) and this is linked with gender inequalities in labour market participation and employment conditions experienced during women’s younger years (Ginn and Arber, 1993).

### 1.2.5 The Third Age framework

Gilleard and Higgs (2002, p. 370) consider the framing of retirement as a ‘Third Age’ period, depicted as a time of opportunity in which individuals can pursue a ‘distinct and personally fulfilling lifestyle’. Any disengagement from society or acceptance of retirement as a marginalised position where one is dependent on the state is seen as a consequence of poor individual choice, rather than a structural outcome of state policy. Gilleard and Higgs (2002) argue for the Third Age period to be positioned within a generational framework rather than one based on class or cohort. It is, claim the authors, the result of rising incomes and material wealth, changing work patterns and greater individual freedom, albeit coupled with a heightened awareness of risk, crime and personal insecurity.
In positioning the Third Age concept in a generational framework Gilleard and Higgs (2002) cite the increased participation of women in the workforce as a defining feature of current retirees. There is, however, no debate as to whether the Third Age philosophy adequately encapsulates retirement for both men and women. Individual choice is an inherent part of the Third Age paradigm, but as was raised in the consideration of the productive ageing and life course frameworks above, the degree to which it is exercised may differ with context and this includes gender. Moen (2011) does consider issues surrounding gender and decision making by positioning the Third Age ideal within the life course framework. She recognises that women gain experience as strategic decision makers throughout the life course as they balance competing demands of employment, family, domestic chores and civic engagement. This experience can be advantageous in the Third Age period as women adjust to what is, currently, considered a ‘not-yet-institutionalized life stage’ with no clear social norms, regulation or legislation (Moen, 2011, p.14). Men, in contrast, tend to take decisions that relate to the economic well being of the family and do so from an employment position that is less fractured than their female counterparts. This continuous work history affords them advantage in terms of pensions and other financial resources, but can make their adjustment to an unstructured Third Age more challenging.

Moen (2011) portrays women’s accumulated experience in strategic decision making as a positive outcome from balancing the competing demands of family and paid employment throughout their life course. However this should not negate the relative disadvantage of any consequential constrained financial situation; older women are more likely to have a higher incidence of poverty and lower incomes than men in retirement due to earlier labour market disadvantage (Ginn and Arber, 1993). Despite their increased participation in the workforce, therefore, the older women of the generation recognised by Gilleard and Higgs (2002) may have fewer financial resources and more constraints on their time than their male counterparts due to their continued responsibility for domestic work. Women may well have accumulated more experience in strategic decision making, and this may smooth their adjustment to retirement, but time and financial limitations constrain their ability to exploit opportunities that could lead to the desired ‘distinct and personally fulfilling lifestyle’ articulated in the Third Age model.
1.2.6 Decision theory

Central to the productive ageing, rational choice, life course and Third Age frameworks described in previous sections are the concepts of decision making and choice. Retirement may not always be a choice with labour market exit the result of involuntary limiting circumstances, and if there is any element of choice decisions might have to be made within constrained environments due to family demands or financial concerns. Gender differences in these circumstances and experiences can lead to older women and their spouses negotiating their respective retirement and labour market exit from inequitable positions. Three hypotheses can inform this process in these situations: the patriarchal, the female dominance and the sphere of interest theories.

The patriarchal hypothesis states that the spouse who holds the most valuable resources has the greatest influence in negotiations (Henkens, 1999). This is relevant to Mann’s (2001) social divisions of welfare approach discussed in Section 1.2.2, which draws attention to gender differences in the proportion of men and women who receive public, occupational, private and informal welfare. Women’s role as informal welfare providers often leads to dependency on a partner or spouse for financial support in later life and in such ‘male breadwinner’ households the retirement decisions of men tend to dominate those of their female spouse (Henkens, 1999; Denaeghel et al., 2011).

The female dominance explanation contradicts the patriarchal hypothesis as it considers social, rather than financial, resources. The marital relationship provides an important support system in retirement, but women are more likely than men to have a support network outside of the marriage (Henkens, 1999). Male partners consequently become more dependent on their spouse during, and after, the retirement transition. This gives women more influence in the decision making process. The third hypothesis - not specific to gender - allocates the balance of power in negotiations to the partner for whom retirement has the greatest consequence. This ‘sphere of interest’ theory states that the person eligible for retirement first has the greatest influence throughout the process.
1.2.7 A multilevel perspective

The household context in which any decision making and retirement process takes place is one of several that influence later life employment patterns - the economic, policy and workplace domains are also relevant. Szinovacz (2012, p. 167) provides a hierarchical conceptual framework in which these can be placed. At the microlevel Szinovacz positions the socioeconomic, career and health trajectories of individuals and families. Social security regimes and labour market structures are placed at the macrolevel and organizational and employer influences are on the mesolevel. The processes that are positioned within each of the micro, meso and macro levels are not independent either from each other or from those on the alternative levels. An individual’s health trajectory, for example, may influence the course of their own retirement pathway as well as that of their partner or spouse. Shared family circumstances could determine each individual member’s employment patterns; financial obligations associated with dependent children are an example of this. Interaction across levels is seen in the dependency of older women on their spouse or partner for economic wellbeing in later life. As raised in the earlier exposition of the social divisions of welfare framework, women are more likely to provide informal welfare through family care and this can disrupt their employment trajectories, reduce their ability to accumulate both occupational and state pension rights and subsequently encourage reliance on joint household resources in retirement (Mann, 2001). This illustrates interaction between women’s employment and family circumstance on the microlevel, workplace pension provision on the mesolevel and the state pension structure on the macrolevel.

The multilevel perspective considered here reflects the complexity of retirement, representing a life course approach and decision making process within the requisite contexts, and advancing the underdeveloped frameworks described by Phillipson (2004). However Szinovacz (2012, p. 152) cites the ‘paucity’ of research that has been conducted using this conceptualization; the literature is dominated by single level studies that do not adequately capture the retirement process. In this thesis a two level framework is constructed with the lower level comprised of repeated observations of women’s, partner and joint household characteristics. Time invariant attributes are positioned at the upper level. This structure allows employment, health, wealth and other factors of interest to be depicted as dynamic.
entities that can change in status or value as women age. The family and household context raised in Szinovacz’s (2012) exposition, as summarized above, is reflected with the inclusion of male partner and joint couple measurements. These can be positioned at either the lower level as time dependent or upper level as fixed quantities. The advantage of this particular structure is that women’s retirement is conceptualised as an evolving process dependent upon wider, and developing, personal and domestic circumstances.

1.3 Conceptualizing and measuring retirement

In the multilevel perspective discussed in the previous section, retirement is conceptualized as a process, rather than an abrupt event. Everingham et al. (2007) identify two models that describe how the retirement process may unfold for older women. The first is a transitive model, in which women reduce their hours of work until the point of complete labour force withdrawal. The beginning of retirement in this instance would be identified as the point at which hours of work are changed. The second model represents a transformative process. In this framework the type, and not necessarily hours, of work is changed. The start of retirement in this approach is signified by an adjustment to the employment task undertaken. In addition to a change in hours or task, Everingham et al. (2007) find that some women consider their retirement to have commenced when their spouse identifies as retired, even if they themselves remain in paid employment. The measurement of retirement is also discussed by Banks and Smith (2006), who identify receipt of pension income and self reported status as two additional indicators of when the process may have commenced.

From the above, there is clearly no one single indicator of the beginning of the retirement process. This is commensurate with Everingham et al.’s (2007) finding that women are often uncertain and ambivalent about being retired. Responsibility for domestic chores, informal care, unpaid volunteer work or continued part time employment can mean that women have no clear transition or demarcation between a working and non-working life, and may refer to any of the above measures when deciding how to describe their labour market position. Some may have difficulty in knowing whether they are retired or not and, as such, retirement for women can be considered a subjective state.

Price and Nesteruk (2010) identify a group of women who follow a ‘disenchanted’ path-
way out of the labour market, characterised by unexpected events and circumstances. Work exit for these women is considered a forced, involuntary event arising from health problems, economic downsizing or significant caring obligations. Resources for older people on this pathway are often constrained, leading to disappointment and disenchantment as earlier expectations of living standards in retirement are not met. Increased participation in the workforce has resulted in a greater proportion of women becoming eligible for, and receiving, social security payments and consequently disability insurance may provide an alternative exit route out of the labour force (Kemp and Davidson, 2009; Banks et al., 2015). This trend is discussed in more detail below, in Section 1.5.2.2. Adequate wealth and financial resources, in contrast, are associated with a greater level of control and voluntariness in retirement timing, and a higher incidence of joint retirement amongst couples (Loretto and Vickerstaff, 2013).

Collectively the studies discussed here point to multiple and distinct retirement pathways for women, defined by the level of personal choice in the timing of the employment transition. However evidence for these differential retirement trajectories has, to date, not come from empirical analysis; the research cited above use qualitative methods. Comparing the characteristics of women who experience involuntary events with those that make voluntary transitions would contribute statistically rigorous evidence for such pathways, and allow for the impact of caring obligations, poor health and financial circumstances to be measured and quantified.

1.4 Long term trends in later life employment

The long term trend in UK employment, unemployment and inactivity rates for different age groups and genders are described here. The focus is on the labour market participation of older men and women aged between 50 and the state pension age; for men this is 64 and for women in 2010 it is age 59. For comparative purposes trends are also discussed for the wider working age population of 15 to 64 for men and 15 to 59 for women. Graphs of employment, inactivity and unemployment rates are presented next with period and cohort effects discussed following that.
1.4.1 Trends in employment, inactivity and unemployment rates

The employment rate used here is defined as the proportion of persons in each age group that worked for at least one hour per week. In Figure 1.1a employment rates for the years 2001 - 2011 are plotted in red for women aged 15 - 59 and 50 - 59, and in black for men aged 15 - 64 and 50 - 64. Older women have an increasing rate of employment and this contrasts with the relatively constant trend shown for the wider female population. The proportion of older men aged between 50 and 64 in work increased and then decreased over this time; again this is a differing trend from the decreasing rates observed for men aged 15 - 64.

Disney and Hawkes (2003) find a positive correlation between gross domestic product (GDP) and employment rates of older people, but while observed trends between 2001 and 2007 reflect this relationship, labour market behaviour during the downturn of 2008 - 2011 does not. During this recession GDP fell further, faster and for longer than in any previous recession and yet the employment rates graphed in Figure 1.1a show increasing proportions of older women were working throughout these years. The employment rate for men aged 50 to 64 fell by only 1.8 percentage points; this is a similar fall to that observed in the 15 to 64 year old male population.

Further evidence that labour market behaviour in this recession differs from that of past is seen in inactivity rates plotted in Figure 1.1b. In past United Kingdom recessions older workers were encouraged to leave the labour force by retiring early, often on health grounds (Gregg and Wadsworth, 2010a) and women more likely to become inactive due to caring responsibilities. However inactivity rates for women aged 50 - 59 have continued to fall as they were prior to 2008, and at a greater rate than that observed within the 15 - 59 year old female population. The proportion of men out of the labour force increased by only 1.3 percentage points during these recessionary years. This evidence is commensurate with the claim of Gregg and Wadsworth (2010a) that employers have not used early retirement as a mechanism for adjusting their workforce in response to this downturn. Conversely, unemployment rates have risen since 2008 (Figure 1.1c). The proportion of men aged 50 to 64 and women aged 50 to 59 actively seeking work increased after the recession began, suggesting that individuals who did lose their jobs during the downturn looked to re-enter paid employment rather than leave the workforce via retirement or ill health.
Figure 1.1: Long term trends in employment, unemployment and inactivity rates

Source: Eurostat (2012)
1.4.2 The influence of period and cohort effects

Given that a strong economy doesn’t explain growth in female employment rates of those aged 50 and over between 2008 and 2011, other factors have been influential. Several cohort and period effects have contributed to the increased supply of older persons to the labour market both in the prior period of economic growth and also during the downturn. Later cohorts of women tend to be more highly educated, with longer periods of education associated with greater labour force participation rates (Hotopp, 2005). Declining fertility rates and a shift towards having children at a later age have contributed to women spending more time in the workforce and therefore having a greater likelihood of working in later life (Department for Work and Pensions, 2005).

From April 2010 the state pension age of women began to incrementally rise from 60 to 65. The first stage of this process saw an increase from age 60 to 61 and analysis by Cribb et al. (2013) associates this with a rise in the employment rate of 60 year old women and their male partners, of 7.3 and 4.2 percentage points respectively. This change in legislation also accounts for a 1.3 percentage point increase in the proportion of women actively seeking work. These increases in employment are equally divided between full and part time workers, and combined with the rise in unemployment are offset by a fall in the percentage of females classified as retired, with no statistically significant change to the proportion reported as sick or disabled or inactive due to caring responsibilities.

Another change over recent years is the expansion of defined contribution rather than defined benefit pension schemes. This is also likely to have decreased early retirement rates and increased labour force participation as defined contribution schemes are not associated with a specific age at which benefits are claimed (Disney and Hawkes, 2003). This is discussed further in Section 1.6.1.4.

The recessions of the 1980s and 1990s saw significant job losses in the manufacturing sector, and this has been repeated in the 2008/09 recession (Jenkins, 2010). However a shift in the UK economy towards the service sector in the intervening years has resulted in a smaller proportion of the older population working in manufacturing and therefore relatively fewer job losses. This shift may also have benefited older workers as jobs in these industries are less physically demanding and more flexible (Disney and Hawkes, 2003).
The steady increases in older men’s and women’s employment rates in the United Kingdom have so far been explained by the economic cycle and cohort effects. Also influential are labour market policies and social security provision; these form part of the institutional context that is discussed in the next section.

1.5 The institutional context

Labour market policies and regulations, unemployment insurance, disability benefits and pension provision together form the macrolevel institutional context in which older people make employment and retirement decisions. The labour market structure and social security provision in the UK are explained in the next two sections.

1.5.1 Labour market structures

Employment protection legislation determines how difficult it is for employers to amend their staffing levels in response to the economic climate. Firms can adjust labour input either externally through changes in staff numbers or internally by adapting hours of work. The United Kingdom labour market is regarded as having a high degree of external flexibility with minimal job protection and as such, it would be expected that firms adjust to challenging economic circumstances by reducing staff numbers. However unemployment statistics for workers aged between 50 and state pension age presented in Section 1.4 showed less than expected increases in the recessionary period. In this downturn adjustment was evenly divided between staffing numbers and hours with Loretto et al. (2013) confirming that UK employers have used a range of flexible working and flexible retirement options to manage their staffing levels, although this comes with the caveat of limited generalizability due to small sample size.

If evidence from the trends in employment, unemployment and inactivity rates discussed in Section 1.4 is considered alongside the labour market features described here, then the participation rate of the older person population has been maintained in the recessionary years despite the low level of employment protection and job seeking support available in the system in which they operate. This is commensurate with the findings of Gregg and Wadsworth
(2010a, p. 38) and Möller (2010). These authors discuss the relationship between employment losses and labour market flexibility in the 2008/09 recession, and find no evidence of a relationship between the level of flexibility in a country’s labour market and employment losses.

### 1.5.2 Social security regimes

Individuals exiting employment enter labour states of inactivity - incorporating retirement, work limiting health conditions and caring roles - or unemployment. These pathways are defined by varying levels of state support with different eligibility criteria, incentives and disincentives determined by state and private pension provision, disability insurance and unemployment benefits.

#### 1.5.2.1 State and private pension provision

Pension provision in the United Kingdom is a multipillar construct comprised of a state funded pension and private occupational and personal retirement funds. A basic pension provides the first tier state provision; this is supplemented with a second tier pension and a means-tested benefit that targets the poorest pensioners. The cohort of women in this research are eligible for the state pension from the age of either 60 or 61 depending on month and year of birth. For men the eligibility age is 65. It is not possible for UK older workers to receive the state pension prior to the official pension age, and entitlement to the full basic pension is determined by sufficient contribution years. These are gained either by working or through credit for periods of childcare or unemployment. Enrolment in the second state supplementary pension is not mandatory and workers may voluntarily opt out and contribute instead to a private fund - although access to such funds is highly selective and largely determined by factors including industry, occupation and firm size.

Limited research is available into the incentive effects provided by the pension system on women’s retirement in the United Kingdom. Available literature does acknowledge the difference in pension resources between genders; women are more likely to work in jobs that limit their opportunity to accumulate pension entitlement and spend more time out of the workforce, and consequently accumulate less state and private pension entitlement than
their male counterparts (Blundell and Johnson, 1999; Ginn and Arber, 1999). Blundell et al. (2002) examine the relationship between pension entitlement and labour force exit for men and find evidence of significant effects. Blundell and Johnson (1999) compare retirement probabilities for both men and women with and without occupational pension schemes, and conclude that women with this type of pension are more likely to remain in the labour market than those without; however that finding is based on descriptive analysis of proportions, with no adjustment made for personal or household characteristics that may explain some of the variation in participation rates.

1.5.2.2 Disability and unemployment: alternative retirement pathways

There is no formal provision for early retirement in the United Kingdom, with pension entitlement available only from the specified state pension age. Leaving employment prior to this depends on either claiming disability or unemployment benefits, or having sufficient personal or household financial resources to fund retirement. Higher financial incentives and less stringent eligibility criteria for disability claims have contributed to a greater proportion of persons entering retirement through this route than through unemployment; statistics from Banks et al. (2011) for 2007 illustrate this point. In that year 25% of men and 13.8% of women aged between 65 and 69 had entered retirement from disability, with 10.8% of men and 8.2% of women transitioning from unemployment to retirement. Additionally 14.8% of women entered retirement through other means.

The use of the disability insurance route as an exit from the workforce was a feature of labour market response to the UK economic downturns of the 1980s and 1990s, to keep unemployment figures low. However as discussed in Section 1.4 aggregate inactivity and unemployment figures for persons aged 50 to state pension age indicate this has not occurred in the recession of 2008/09. Rather, unemployment rates have risen and inactivity rates have remained relatively stable or fallen. Gregg and Wadsworth (2010b, p. 50) suggest that policy reforms made in 2008 to disability insurance may have influenced this, with the introduction of the Employment Support Allowance (ESA) and more stringent Work Capability Assessment test restricting enrolments in ESA and contributing to the rise in unemployment claims during the recession. A shift to a service economy and away from
manufacturing may also have had an impact, as service professions do not lead as easily to this exit route.

The disability pathway for UK women is becoming more prominent as increasing participation in the labour force results in greater numbers meeting the eligibility criteria for disability benefits. Kemp and Davidson (2009) report that between 1995 and 2004 the number of females of working age claiming incapacity benefit increased by 35% compared to a 2.5% increase in the proportion of working age male claimants. However, recent research from Banks et al. (2015) shows a decrease in the benefit receipt rates of women aged 55 - 59 since 2010. Banks and Smith (2006) identify differences in retirement pathways for persons with varying financial resources. Eligibility for disability insurance is determined by contributions and benefits are not earnings related; thus, for low income earners benefits have a high income replacement rate. This, combined with no extensive unemployment provision, has resulted in the disability insurance pathway being used as a substitute early retirement route primarily for those from the lowest end of the wealth distribution.

Kemp and Davidson (2009) emphasize the scarcity of research on the characteristics and circumstances of female beneficiaries and the routes they take onto incapacity benefit. Their own work investigates these issues for women aged 16 to 59 and finds significant differences between genders in the factors associated with moving from employment to disability benefits, citing particularly the family and caring responsibilities of women. Banks et al. (2015) also emphasize the difficulty of examining older women’s employment patterns given the complex combination of long term trends, the recent recessionary period and reform of disability insurance schemes. More research is required to examine the characteristics, beyond wealth, associated with women’s transitions between employment and disability for women aged 50 and over.

### 1.6 Individual and household level predictors of later life employment

The macrolevel context discussed in the previous section outlined available pathways out of employment in the United Kingdom, and the possible relationship between macrolevel
factors and later life employment. However not all individuals will retire by formal routes; for example women’s child bearing and work histories contribute to them frequently following non standard trajectories dependent on partner’s circumstances. Loretto and Vickerstaff (2013, p. 65) describe this process as ‘often messy and disrupted’ with periods of employment alternating with time spent out of the workforce attending to family obligations.

The point at which the retirement process is considered complete also differs between individuals. Banks and Smith (2006, p. 43) discuss three events which could define the transition point between not being retired and being retired - the complete and permanent withdrawal from employment, receipt of private or state pension and the time at which a person perceives themself to be retired. But regardless of the end point of the process the individual and household factors impacting on both older women’s and men’s retirement routes can be grouped into those relating to economic feasibility, non voluntary retirement, disposition and attitudinal factors and long term context (Szinovacz and Deviney, 2000, p. 479).

1.6.1 Economic feasibility of retirement

The economic feasibility of retirement depends on an individual’s or couple’s current financial situation - as determined by personal and household state and private pension resources as well as non-pension wealth - and the expected number of years they would need to fund retirement for.

1.6.1.1 State pension income

Although coverage of the UK state pension is close to universal with nearly all households receiving some benefit, the dependence on years of contributions and marriage has resulted in many women failing to qualify for the full entitlement. Discontinuous work histories, part time work patterns and claiming through their husbands rather than in their own right have caused inequality between women and men in the level of pension received. Figure 1.2 shows this variation - in September 2008, 48% of female pensioners received a full basic pension compared to 87% of men. Thirty one percent of women pensioners received less than 60% compared to 2% of males (Office for National Statistics, 2009). More women receive income from the second supplementary state pension than men, but the net median weekly amount
they are entitled to is less than half that of their male counterparts. These disparities between men’s and women’s state pension payments can lead to wives and female partners depending on total family, rather than their own individual, pension wealth for retirement income.

![Figure 1.2: Proportion of pensioners on different percentages of basic state pension](source: Office for National Statistics (2009))

Table 1.1: Annual pension payments for pensioner couples in 2008/09 (£)

<table>
<thead>
<tr>
<th>Type of pension</th>
<th>Mean</th>
<th>1st quartile</th>
<th>Median</th>
<th>3rd quartile</th>
<th>3rd to 1st quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>State</td>
<td>9,800</td>
<td>8,400</td>
<td>9,500</td>
<td>11,100</td>
<td>1.32</td>
</tr>
<tr>
<td>Private</td>
<td>11,200</td>
<td>3,200</td>
<td>7,200</td>
<td>14,800</td>
<td>4.63</td>
</tr>
</tbody>
</table>

Source: Office for National Statistics (2010)

Summary statistics of annual state and private pension payments made in 2008/09 to pensioner couples are in Table 1.1. Note that the median value of state pension payment, of £9500, is similar to the mean amount of £9800 and this suggests that couples who are entitled to the highest level of state pension payment do not receive considerably more than their counterparts that are paid the lowest level of entitlement. The relatively even distribution of state pension income across households is also reflected in the ratio of the third to the first quartile of 1.32. A higher value of this ratio indicates greater variation in the amount received by coupled households.

A further point to note about the state pension is the relationship between the amount
pensioners receive and their previous pre-retirement income. The OECD (2011) provides income replacement rates for the United Kingdom. Defined as the ratio of a population’s average pension to the average income, an average earner in the UK receives state pension benefits that are 31.9% of their pre-retirement earnings. This is low when compared to other European countries; as two illustrative examples, the replacement rate for an average German earner is 42.0% and 79.7% for the equivalent in Denmark. Explaining the difference between the low UK rate and high Danish rate is the inclusion of private pension wealth that is compulsory for employees to subscribe to in Denmark.

This section has shown how older females are likely to be dependent on total family pension income for financial support, and that the state pension component of this is evenly distributed across households. However the state pension does have a low value compared to pre-retirement earnings, and this can result in reliance on private pensions to ensure adequate retirement income (Office for National Statistics, 2011). Private pension resources of couples in the UK are detailed in the next section.

1.6.1.2 Private pension income

The importance of private pension wealth to UK retirees is seen in Figures 1.3a and 1.3b. Figure 1.3a shows the composition of family combined state and private pension wealth across pension wealth decile groups, with private pension sources divided into that from defined contribution schemes, defined benefit schemes and past pensions. The even distribution of state pension wealth across the deciles is evident, but considerably more heterogeneity can be seen in the increasing amount of private wealth held by the richest deciles, compared to very little in the poorest three. This is observed also in Figure 1.3b. The proportion of total household pension wealth that comes from each pension source is shown here with households from the lowest decile groups relying largely upon the state pension. An estimated 33% of pensioner couples received no payments from private sources in 2008/09 (Office for National Statistics, 2010, p. 5).

Summary statistics for the annual private pension payments to pensioner couples are given in Table 1.1 on page 39. The mean private pension value is £11,200 per year, but the median amount is lower at £7,200; this is a skewed distribution with some couples receiving
(a) Mean family pension wealth according to pension type, n = 4687 individuals aged 50 - state pension age

(b) Composition of wealth holdings, n = 4687 individuals aged 50 - state pension age

Figure 1.3: Family pension wealth and total wealth holdings by decile group

Source: Banks, Emmerson, Oldfield and Tetlow (2005)
considerably more private pension income than others. This finding is commensurate with the heterogeneity discussed above, and further evidence is given by the ratio of the third to the first quartile of couple’s private pension income, of 4.63. This is considerably greater than the state pension ratios of 1.32 and confirms that state pension income is more evenly spread across pensioner couples than income from private sources is.

This analysis of private pension wealth and income has identified a source of heterogeneity in the retirement resources available to older women and men. As determined earlier, women’s financial support in retirement is associated with total household resources. However when total wealth is broken down into state and private sources considerable variation is seen across couples only in the private component - more affluent households have a high proportion of private wealth and poorer families have no, or little, such provision. Considered in the next section is the possibility of a relationship between these different levels of private pension wealth and the likelihood of older women remaining in employment; whether the economic feasibility of retirement is reflected in the labour market behaviour of women from couples with varying degrees of private pension wealth.

1.6.1.3 The association between pension wealth, household composition and employment status

Table 1.2: Distribution of total pension wealth for families aged 50 - state pension age, by employment status (£000s)

<table>
<thead>
<tr>
<th>Employment status</th>
<th>Mean</th>
<th>1st quartile</th>
<th>Median</th>
<th>3rd quartile</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>One partner in paid work</td>
<td>338.3</td>
<td>156.8</td>
<td>260.7</td>
<td>424.2</td>
<td>1,066</td>
</tr>
<tr>
<td>Both in paid work</td>
<td>328.8</td>
<td>157.5</td>
<td>260.2</td>
<td>437.9</td>
<td>2,010</td>
</tr>
<tr>
<td>Both retired</td>
<td>571.9</td>
<td>278.7</td>
<td>384.9</td>
<td>659.5</td>
<td>168</td>
</tr>
<tr>
<td>Both other inactive</td>
<td>244.3</td>
<td>118.7</td>
<td>182.8</td>
<td>313.0</td>
<td>444</td>
</tr>
</tbody>
</table>

Source: Banks, Emmerson, Oldfield and Tetlow (2005)

The association between domestic context, total family pension wealth and employment status is examined by Banks, Emmerson, Oldfield and Tetlow (2005, p. 20). Table 1.2 contains summary statistics for the total pension wealth of couples aged 50 to state pension age according to employment status. The median level of state and private pension wealth for families with one partner working is £260,700. This is only marginally higher than the
median level of £260, 200 in households with both partners working. These two household types - which fall in the central wealth decile groups - are likely to have similar proportions of private pension provision despite the non-employed status of one person in the first household type. Research into employment habits of this group is limited; Loretto et al. (2005) term older workers in these central wealth deciles the ‘missing middle’, because studies of this age group mostly focus on those at the extreme ends of the wealth distribution. From the qualitative study of Loretto and Vickerstaff (2013, p. 69) a possible relationship between family income and women’s work is suggested, in that women tend to come ‘in and out of the labour market depending upon childcare and other caring responsibilities and to support the family income’. If having sufficient family income in retirement is dependent on private pension provision, then the likelihood of a woman from these middle wealth deciles staying in work might be negatively related to private pension wealth; the lower the level of household private pension resources, the more likely she is to remain in work.

Two person households in which neither member is in paid employment are further divided into two groups in Table 1.2. Firstly, those in which both the man and woman describe themselves as retired - this group has the highest median household total state and private pension wealth of £384,900. This group are likely to have a high proportion of private pension wealth, which is commensurate with the conjecture above that a higher level of private pension resources is associated with a lower likelihood of an older woman working. The second group is comprised of members who are not retired and yet also not working; these households might have originated as either single or dual earner families in which job displacement or illness and associated caring responsibilities have led to involuntary labour force withdrawal. These couples are most likely to rely on disability insurance for support prior to state pension age and with the lowest median total pension wealth of £182,800 will depend largely on only the state pension in retirement. For this group any relationship between private pension wealth and employment chances would not apply, as their retirement trajectories are driven more by the above mentioned involuntary events. These involuntary factors are discussed further in Section 1.6.3.
1.6.1.4 Defined benefit and defined contribution pensions

The economic feasibility of retirement is influenced by the specific type of private pension an individual subscribes to. Lagoutte and Reimat (2013) summarize the two categories. Defined contribution (DC) schemes are funded by contributions from employees and employers with benefits usually provided by converting the fund into an annuity, whereas income from defined benefit (DB) schemes depends on the length of career and end of career salary. Defined contribution schemes are becoming more prevalent in later cohorts, but as seen in Figure 1.3a (page 41) UK families in the highest deciles of mean family pension wealth have the greatest proportion of their private pension wealth from DB, rather than DC schemes. In 2008/10 28% of households with wealth in private pensions held a current occupational DB scheme with 14% contributing to an occupational DC fund (Office for National Statistics, 2012).

The risk to the beneficiary with regards to retirement income differs between the two scheme types. Income from a DB pension is guaranteed for life, but benefits from a DC fund are reliant on investment returns and the annuity rate at conversion with the associated risk borne by the recipient (Banks et al., 2011; Lagoutte and Reimat, 2013). Consequently individuals subscribed to a DC pension find it more difficult to predict their retirement income than those with a DB arrangement - Crawford and Tetlow (2012b, p. 23) report that 36% of DC subscribers were unable to estimate their retirement income compared to 28.2% of DB pension members. Forty five percent of DC scheme holders could state an exact amount that they expect to get on retirement, less than the 58.9% of DB members. Furthermore, evaluating benefits from defined contribution schemes is more difficult for women than men.

Evidence suggests that individuals enrolled in defined benefit schemes tend to retire at state pension age or at the age defined by their pension scheme, whereas retirement ages for those in defined contribution schemes are less determined by incentives offered at particular ages, and are associated with longer periods of employment (Banks and Smith, 2006). This effect may have been exacerbated by the recession of 2008/09. As Crawford and Tetlow (2012b, p. 19) explain, any individual with an unannuated DC pension fund will be affected by the prevailing asset prices and, according to Lagoutte and Reimat (2013, p. 3), these have depreciated during this period and this has ‘severely penalised’ DC fund holders. These authors contend that to avoid receiving a reduced pension affected persons must post-
pone retirement until the losses are partly offset. They imply that the better than expected employment rate of 59 - 64 year olds between 2007 and 2009 is associated with this, but provide no supporting evidence.

This section has shown that the economic feasibility of retirement is influenced by the type of pension subscribed to, and that those in DC schemes - particularly women - might find evaluating economic feasibility more difficult. The consequences on women’s later life employment might be that women in households with large proportion of DC pension wealth are more likely to remain in paid work, with this effect stronger since the economic downturn began in 2008.

### 1.6.1.5 Non pension wealth

Banks, Emmerson and Oldfield (2005, p. 18) establish a positive correlation between family non-pension wealth - for example, housing or business assets - and expected family private pension income. While the main source of retirement funding is pension wealth rather than the drawing down of non-pension wealth (Crawford and Tetlow, 2012a), the relationship found by Banks, Emmerson and Oldfield suggests that any individual who experiences a change in the value of their non-pension wealth might also change their expectations with regards to private pension income. Crawford and Tetlow (2012b, p. 21) find that the average value of housing wealth has varied during the period of interest, with a ‘significant increase’ between 2002/03 and 2004/05, but a decline in average real housing wealth coinciding with the recession of 2008/09. Families might, therefore, have adjusted their expectations of private pension income downwards over the course of the economic downturn in response to any perceived fall in value of housing asset value.

### 1.6.1.6 Expectations of life expectancy

The economic feasibility of retirement can depend on the length of time retirement needs to be funded for. This issue was first raised in Section 1.2.3 in the discussion of rational choice theory and its application to retirement decisions. Research cited there found that 59% of individuals aged between 50 and 64 and still in work had not considered the number of retirement years they would need to finance (Crawford and Tetlow, 2012a). Other studies
examine life expectancy and people’s predictions of working at a given age, and how these differ according to wealth. Banks, Emmerson, Oldfield and Tetlow (2005) find that less wealthy individuals expect to die sooner on average than those in the richest deciles, but men aged 50 - 59 and women aged 50 - 54 in both the poorest and highest decile groups report the lowest mean chance of being in work five years before the state pension age.

Table 1.3: Absolute life expectancy at age 50 by gender, 2005 - 2011

<table>
<thead>
<tr>
<th>Gender</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Women</td>
<td>32.9</td>
<td>33.3</td>
<td>33.4</td>
<td>33.4</td>
<td>34.0</td>
<td>34.1</td>
<td>34.5</td>
</tr>
<tr>
<td>Men</td>
<td>29.5</td>
<td>29.8</td>
<td>30.0</td>
<td>30.2</td>
<td>30.7</td>
<td>30.9</td>
<td>31.2</td>
</tr>
</tbody>
</table>

Source: Eurostat (2013)

Absolute life expectancy statistics for the United Kingdom are presented in Table 1.3 and show a clear gender difference (Eurostat, 2013). There is a long term increasing trend in the mean number of years that both men and women can expect to live from the age of 50; however the gender gap is persistent at approximately 3.3 years higher for women. Based on these figures a 50 year old woman in 2011 the UK would need, on average, sufficient retirement income to support themselves until the age of 84.5, whilst her male counterpart would need support until the age of 81.2. This has implications for women’s quality of life in older age; they tend to have lower financial resources than their male counterparts (Ginn and Arber, 1999), but on average, live longer.

1.6.2 Employment history and working patterns

Older women’s labour market attachment is associated with working patterns established earlier in the life course (Szinovacz and Deviney, 2000; Pienta, 2003). Continued participation in the workforce throughout the child bearing years is indicative of strong labour market attachment, which can persist in later life and contribute to delayed retirement. The form of this participation may differ amongst women, however, with some adopting part time rather than full time hours in order to care for their children.

Part time work amongst older women can also be characteristic of a particular pathway to retirement that involves the gradual end from full time working life rather than an abrupt
disengagement, with part time ‘bridge jobs’ spanning the time between full time engagement and complete labour market withdrawal (Cahill et al., 2006). Motivation for older women reducing work hours may arise from a preference for shared leisure if their spouse or partner retires, from their own poor health, or in response to an increase in the need to care for a spouse, partner or elderly relative.

A third employment pathway involving part time work may be observed among women previously disengaged from the labour market. Women’s work hours is one margin that couples may adjust in response to household circumstances, and women formerly out of the labour market might rejoin the work force in a part time capacity to supplement the family income should household financial resources be insufficient for their needs.

Long term employment conditions and contextual factors can impact on women’s ability to accrue both state and pension resources. As established in Section 1.6.1, women tend to have lower entitlement to state pension income than men, but this applies also to private pension wealth. Ginn and Arber (2002) examine women’s private pension coverage and its association with occupational class, education level, caring responsibilities and part time working. They find that access varies with occupational group and this causes a particular limitation for women who work part time; not only might part time workers be concentrated in low skilled, low paid jobs with less private pension availability, it was also only in 1994 that legislation was passed giving part time workers the same rights to private pension access as their full time colleagues (Bardasi and Jenkins, 2010). Women with breaks in their employment history are less likely to join occupational schemes because of challenges in transferring pensions between employers, and for those who can access private pensions the level of wealth they are able to accumulate is dependent upon their income. Again, part time working and breaks in employment records will influence this; on average women have lower work hours and rates of pay than men and these translate into lower pension income (Bardasi and Jenkins, 2010).

The tendency for women to have discontinuous and part time work histories is attributed to childcare and caring responsibilities. However, whilst women with children have a ‘substantial loss’ of private pension entitlement compared to their childless counterparts, their education level can moderate this effect (Ginn and Arber, 2002). Graduate women have
the least loss to entitlement and women with mid-level education the greatest; those with a low level of qualification fall between these, indicating a non-linear relationship between education level, motherhood and private pension coverage.

The issues discussed here are also applicable to some male partners in coupled households. Men in certain occupational sectors and low paid jobs will also be restricted in their ability to accumulate private pension wealth, with workplace schemes typically available to the highly educated, professional, full time workers with sufficient years of service.

1.6.3 Non voluntary factors

The two main reasons for involuntary early retirement are ill health and job displacement. Banks and Smith (2006) find that amongst people who reported their retirement as forced, 56% of men and 45.5% of women gave their own ill health as the main reason, with 28.2% of men and 20.6% of women citing redundancy. Others‘ ill health was also a common explanation for women to be forced into early retirement; 17.6% stated this reason compared to only 3.8% of men. In reality the decision to leave employment can be influenced by more than one of these involuntary events as well as other factors - in particular finance, as Loretto and Vickerstaff (2013) find in their qualitative study of retirement trajectories. For one interviewed couple two successive redundancies prompted the husband to retire from paid work, with his wife retiring a short time later as she developed a serious health condition soon after being made redundant. In a second family, the husband’s forced early retirement because of ill health caused his wife to move from part time to full time work mainly for financial reasons, although also partly for the stimulation of going to work each day. The interaction between poor health and financial resources is examined here, and attitudinal factors discussed further in Section 1.6.4.

The spousal response to the onset of poor health is unlikely to be the same across all families, particularly if the effect is modified by household financial resources. In the UK between household variation in retirement income is related to private pension wealth, meaning an association between partner employment status, health and private pension wealth can be hypothesized. Individuals in the lowest wealth deciles tend to have no private pension resources and are more likely to have poor health; should a health condition lead to exit from
the labour force disability insurance provides the main source of income (Banks and Smith, 2006). However the proportion of income from paid work that disability benefits replace is high for low wealth families, meaning disability insurance might provide adequate income in which case the female partner is more likely to leave work and care for her spouse in these instances. The employment status of these couples can then be described as ‘both not working but not retired’ and they form part of the group with lowest family pension wealth identified in Section 1.6.1.3.

At the upper end of the wealth distribution households have a larger component of private pension resources. Wealthier people tend to be healthier (Banks, Emmerson, Oldfield and Tetlow, 2005), but should the husband develop a work limiting health condition his spouse is also more likely to leave work to care for him having already accumulated sufficient resources to ensure financial well being. This group form the early retirees discussed in Section 1.6.1.3. It is women from the middle decile groups for private pension wealth that may have the highest probability of staying in work should their partner leave work on health grounds. They face a relatively lower income replacement rate and are least likely to have the level of private pension funds required to ensure continuity of standard of living in retirement.

Quantitative research on the relationship between health, employment and household financial resources on women’s employment is limited in the UK context. German research supports an association between employment and spousal health, with Blau and Riphahn (1999) investigating the chances of continued employment for a coupled woman according to the health and employment status of her partner. If her partner has a chronic illness, but is working, the wife is more likely to remain in employment; if her partner had left the labour force, she also is more likely to not work. This effect is not symmetric however. The husband’s labour market response to his wife having a health condition is independent of her employment status.

The influence of social security provision - and other macrolevel factors of labour market regime and economic context - on voluntary and involuntary retirement rates is investigated by Dorn and Sousa-Poza (2010). They find generous early retirement social security provision is associated with both more voluntary and involuntary early exits, and rigid employ-
ment protection legislation creates employment constraints and therefore a greater incidence of involuntary retirements as firms are less likely to hire. In the context of an economic recession high unemployment rates are associated with an increase in forced retirement, because displaced workers are unable to find new jobs. Whether or not these findings hold for recent cohorts of older workers requires further research; Dorn and Sousa-Poza’s analysis was conducted on individuals who retired between 1983 and 1997 when the specific structure of social security provision and labour market regime were different from the current system.

1.6.4 Attitudinal and dispositional effects

Evidence for this next group of explanatory factors for later life employment comes from Loretto and Vickerstaff’s (2013, p. 75) interviews on later life work and retirement behaviour. One respondent continued working, because she enjoyed the stimulation of going to work each day; others focused more on reasons for leaving employment, with explanations such as the job ‘was just so, so boring and I just hated it’ and ‘if it had been a good job I would have carried on’. These responses reflect the importance of job satisfaction and job quality in the retirement decision making process, and Loretto and Vickerstaff identify them as particularly important for women’s continued employment.

The criteria for a ‘good’ job and job satisfaction are explained by Lissenburgh and Smeaton (2003, p. 20, 26). A ‘good’ job has adequate levels of pay and training, a degree of autonomy and job security; autonomy is also important for satisfaction, along with a sense of achievement and the opportunity for workers to apply their skills. The chances of an older woman having these aspects in her work are associated with her domestic obligations throughout the lifecourse. Caring responsibilities and discontinuous employment histories can lead to women having limited job opportunities in later life, resulting in poorly paid, low skill jobs, little job satisfaction and decreased likelihood of continued employment.

Szinovacz and Deviney (2000) and Kubicek et al. (2010) raise marital quality as influential for couple’s retirement decisions. Strained relationships are more likely associated with delayed labour force exit where individuals perceive the workplace as providing respite from difficult home circumstances. Those in stronger partnerships, however, may hasten retirement in anticipation of enhanced shared leisure time.
### 1.7 The domestic context of single older women

The focus in this chapter has been primarily the employment and circumstances of pensioner couples and women residing with their partner or spouse. The domestic environment of single older women, and how it may differ from those cohabiting, is considered in this section, beginning with financial circumstances. Heterogeneity within the single women’s population is also discussed.

The distribution of state and private pension payments to older couples was detailed in Section 1.6.1. In 2008/09 the mean annual state pension payment to pensioner couples was £9,800 and the mean value of annual income from private sources £11,200. Table 1.4 shows summary statistics of pension income for single female pensioners. The mean annual state pension payment for single women was £5,900 and that from private funds is half that of coupled pensioners, at £5,500. As would be expected, on average there is a substantial difference in the level of financial resources received by single women compared to those coupled, and the absence of a partner’s contribution is one obvious explanation for this.

Table 1.4: Annual pension payments for single female pensioners in 2008/09 (£)

<table>
<thead>
<tr>
<th>Type of pension</th>
<th>Mean</th>
<th>1st quartile</th>
<th>Median</th>
<th>3rd quartile</th>
<th>3rd to 1st quartile</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>State</td>
<td>5,900</td>
<td>4,700</td>
<td>5,600</td>
<td>6,800</td>
<td>1.45</td>
<td></td>
</tr>
<tr>
<td>Private</td>
<td>5,500</td>
<td>1,400</td>
<td>3,500</td>
<td>7,400</td>
<td>5.29</td>
<td></td>
</tr>
</tbody>
</table>

Source: Office for National Statistics (2010)

The presence of a partner can influence older women’s employment transitions by providing an incentive of joint leisure time. A retired male spouse is associated with increased risk of work exit of the female spouse (Szinovacz and Deviney, 2000); this effect is explained by a preference for shared leisure during retirement, but this influence will not be present in single women households. Family caring obligations might also differ with household composition. Coupled women are more likely to have a larger extended family group compared to single females and this wider network may result in greater care demands placed on an older woman should a family member experience poor health. In the advent of a woman’s own poor health or illness, those who are coupled may be more likely to leave work as their...
spouse can provide financial support; single women, in contrast, have only their own financial resources to rely on. The adjustment made to a woman’s employment in response to poor health, therefore, may depend upon her partnership status.

Within the single female population circumstances can also differ, according to financial circumstances and marital status. Figures in Table 1.4 show that whilst state pension payments are reasonably evenly spread across single women households, private pension income is not. The ratio of the third to first quartile of state pension payments for single females is 1.45, compared to 5.29 for private pensions. The wealthiest single women receive considerably more private pension than their poorer counterparts. One potential explanation for this is relationship history, with variation possible between never married, divorced and widowed women. Those divorced or widowed are more likely to have children and associated caring obligations, and consequently more discontinuous work histories, a lower level of labour market attachment and fewer pension rights than women who have never married. Additionally, differences in the financial resources of divorced and widowed women may arise from the circumstances surrounding their transition into living alone. Their situation in retirement may depend upon how recently any divorce or bereavement occurred, and any financial arrangement or bequest from the former spouse.

Emphasised here are differences in the domestic circumstances of coupled and single women, and within the single women population. The presence of a partner can contribute financial assets, but also possible increased caring demands and different retirement incentives for coupled women. Heterogeneity in circumstances arising from marital and relationship history is likely within the single women population. Accounting for these differences in any analysis of the retirement process is difficult to achieve if both coupled and single women’s employment patterns are examined jointly in one modelling framework. Analysis is instead best done separately for each household type, but time and space constraints prevent such an approach being taken in this thesis. Rather, this research will present a thorough investigation of the circumstances surrounding coupled women’s employment transitions. Results and conclusions, therefore, should not be inferred to single women and are limited to cohabiting coupled women and their male partners.
1.8 Research questions and hypotheses

The long term increase in older women’s employment rates in the United Kingdom reflects a change in the composition of the labour force and is particularly significant given the context of the 2008/09 economic downturn. Labour market mechanisms do not explain these developments, as similar trends have been observed in countries with alternative labour market structures. However institutional context is influential in that the state pension structure can result in women accumulating less pension entitlement than their male counterparts, and this encourages dependency on partner and household resources. The majority of UK retirement research does not reflect this dependency, instead concentrating on the impact of individual characteristics on male retirement patterns. International studies from Germany (Blau and Riphahn, 1999; Drobnič, 2002), Denmark (Bingley and Lanot, 2007) and the United States (Szinovacz and Deviney, 2000) confirm the influence of spousal or partner characteristics and total household resources, and failure to incorporate these attributes in UK research may mean that current understanding of later life employment trajectories is incomplete. Findings from qualitative UK studies support this idea, suggesting that the labour market attachment of older women is associated with partner’s health, employment status and household financial resources (Loretto and Vickerstaff, 2013); but these conclusions are not generalizable to the wider population. Establishing the importance of the household context for UK older women’s employment is therefore the first aim of this research:

**Research question 1**  Is labour market exit of women in England influenced by the household context, with partner characteristics and total family financial resources modifying the effects of individual level attributes?

**Hypothesis 1**  Partner’s ill health, partner’s retirement status, and household pension wealth influence the likelihood of women’s labour market exit.

In their study of marital characteristics and retirement decisions, Szinovacz and Deviney (2000, p. 489) contend that ‘women remain in the labour force if and as long as their income is needed for the couple’s economic well-being.’ This suggests voluntary early labour force
exit - which here we identify as exit into reported retirement prior to state pension age - is more likely to be influenced by financial resources than any other predictor of exit. Because state pension benefits are considered low in the United Kingdom private pension wealth plays an important role in retirement income provision. However private pension resources are not evenly distributed across households, leading to heterogeneity in total pension wealth which might be associated with women’s chances of continued employment. This possible relationship between pension resources and women’s work has not yet been comprehensively studied in the United Kingdom.

Women out of the labour force who are not retired are classified as either long term sick or disabled, unemployed or as caring for their home and family. These are collectively known as ‘not working, not retired’ states and are the likely outcome of involuntary factors including poor health of either the woman or her partner, or job loss. The differential impact of financial factors and health on women’s exit pathways is the subject of the second research question:

**Research question 2** Does the impact of male partner characteristics and family financial resources vary across voluntary and involuntary pathways?

**Hypothesis 2a** Household pension wealth has a greater impact on women’s voluntary labour market exit into retirement prior to state pension age than on involuntary exit into alternative non-retired states.

**Hypothesis 2b** Involuntary transitions into non-retired states are influenced more by the health status of a woman or her partner than by household financial resources.

The third research hypothesis concerns the asymmetric impact of spousal health on the employment trajectory of the other partner. If older women’s participation in the workforce is responsive to family obligations then poor health of the male partner could lead to additional caring needs undertaken by the female spouse, and her subsequent transition out of the labour force. The employment of the male partner, however, may be more essential to the economic wellbeing of the family; poor female spousal health could therefore have less of an impact.
on the probability of men’s transitions out of work. These partner health effects are stated formally in the third research question and hypothesis:

**Research question 3** Does spousal health impact equally on the probability of continued employment for older women and their male partners?

**Hypothesis 3** Spousal health has a greater impact on the probability of a coupled older woman leaving work than it does on the transition probability of the male partner.

The methods that will be used to address the above research questions are described in Chapter 2. The first hypothesis is the focus of Chapter 3 with the second discussed in depth in Chapter 4. Male partner transitions are considered in Chapter 5 and following that, in Chapter 6, is a presentation of missing data issues and the sensitivity of results to assumptions made in the analysis. Chapter 7 concludes with a discussion of findings as they relate to the three set research questions.
Chapter 2

Methods

2.1 Introduction

The aim of this thesis is to establish the impact that an older woman’s domestic circumstance has on her employment trajectory. The health of the male partner, his employment status and household pension wealth are of particular interest. The first research question addresses the influence of these factors on the probability that a woman leaves work between 50 and state pension age. The second hypothesis considers the differential effect of health and pension wealth on alternative exit pathways, with higher pension resources expected to influence voluntary exit into reported retirement prior to state pension age, and health likely associated with involuntary exit into alternative non-retired states. The focus of the third research question is on the asymmetric impact of spousal health, with health of the male partner expected to have a greater impact on his wife’s transition probability than the female partner’s health has on her husband’s employment.

The focus of this chapter is on the methods used to address the above research questions. The approach used here is particularly significant as existing research into women’s retirement in the United Kingdom is primarily qualitative in nature (Loretto and Vickerstaff, 2013; Duberley et al., 2014); we extend this by analysing a large scale dataset specifically designed for research into older persons and their families. This dataset, the English Longitudinal Study of Ageing (ELSA, Marmot et al. (2011)), gathers information on several topics including demographics, economics, health and life history. In the next section this is described in more detail; we explain the sampling strategy used to select the ELSA house-
holds analysed in this thesis, and the specific questionnaire items from which outcome and covariate measures are configured. In Section 2.3 the modelling approach and strategy are explained and in Section 2.4 we explain how time will be structured in the analysis; the measurement of time is central to any longitudinal study and the options and chosen structure will be described there. Following that descriptive sample statistics are presented in Section 2.6. The chapter is summarised in Section 2.7.

2.2 Description of data

This research places the dynamic process of ageing within a multilevel context. Repeated individual, partner and household level measurements that reflect this approach are available in ELSA. These measurements are collected bi-annually and are collated in a modular structure with units including individual and household demographics, health, work and pensions, income and assets and a self completion questionnaire. A life history module contains additional retrospective data that gives a detailed picture of life course events related to childhood circumstances, children and partners, employment and health. ELSA is designed to be representative of individuals aged 50 and over living in private residences, and the first five waves of data are analysed for this research. The first wave was collected in 2002/03 with subsequent waves also covering two-yearly intervals; the latest analysed in this thesis was completed in 2010/11. The life history unit was collated in wave 3. To ensure ELSA remained representative of all age groups the study was supplemented with refreshment samples at waves three and four. The first of these sampled persons aged between 50 and 53, whilst the wave four refreshment sampled a wider range of 50 to 74 years.

2.2.1 The selected ELSA sample

A separate ELSA sample is needed for each of the three research questions. Figure 2.1 details the selection process for each sample; for the analysis of women’s transitions and the first research question, this is shown in green. The additional selection step for the second sample and research question are in red, whilst those for the male partner analysis are shaded grey.
The process begins with the identification of households, in each of the first five waves of ELSA, that contain a female member aged between 50 and 59 inclusive. There are 4985 households that meet this criteria. The sample is then refined based on household composition. Women who report as living with a male partner or spouse are retained with those that have no resident partner removed. This gives a sample of 3633 cases.

To detect a transition from employment, sample members must have been observed on at least two consecutive waves and be employed on the first of these. A woman who reports as working at her ELSA interview in wave 1, for example, would be included if she reported either an employed or non-employed status in the second wave. She would not be included if her next response, after wave 1, was at wave 3. A respondent who was not working at wave 1, but working at wave 2, would only be included if she had a third observation available in wave 3. There are 2238 eligible women and households in the sample at this point. A long form person-period dataset is constructed from this sample. Each member is allocated ten records - one for each year of age between 50 and 59 inclusive, giving a total of 22380 entries.

At the fourth stage in Figure 2.1, women’s records for ages younger than the age of first observation are removed. If no transition is observed cases are right censored at either the age of the last consecutively observed wave, or at age 59. Records for years older than the age of right censorship are removed, as are those for years older than the age of transition. As an example, consider a woman who first responded to ELSA in wave 2 at age 52, and then again at age 54 in wave 3, before missing wave 4 and responding for the final time at age 58 in wave 5. In the long form person-period dataset her records for ages 50 and 51 will be removed, as will those for ages 55 onwards. Records for ages 52, 53 and 54 are retained. The person-period dataset contains 9198 records after such deletions are made.

In the previous step, records where women were not observed at age 50 were amongst those deleted. However records for women who were observed at age 50 also need to be removed. This is the minimum age of entry into the sample, all women observed at 50 must be employed, and it is not possible for transitions to be detected at this age. These records should therefore not be included in the analytic dataset, which in practice contains women aged 51 to 59 inclusive. The person period dataset has 8698 entries after the removal of these
English Longitudinal Study of Ageing Waves 1 to 5
Household contains female aged 50 - 59
Number of female cases = 4985

Retain women residing with male partner or spouse at first entry.
Number of female cases = 3633

Females observed on at least two consecutive waves and employed on at least the first of these.
Number of female cases = 2238
Number of female person period records = 22380

Remove records at ages younger than first observation and older than age of censorship or transition
Number of female cases = 2238
Number of female person period records = 9198

Remove records for age 50 where event cannot be observed.
Number of female cases = 2238
Number of female person period records = 8698

Remove records with incomplete covariate information after imputation and lagging.
Final number of female cases = 1569
Final number of female person period records = 6182

Transosed women selected for type of transition analysis.
Number of cases = 287

Male partners from final sample of women’s households.
Number of male partner cases = 1569

Remove men with no observed employment when female partner or spouse was aged between 50 and 59.
Number of male partner cases = 1368

Retain men observed on at least two consecutive waves and employed on at least the first of these.
Number of male partner cases = 1287
Number of person period records = 12870

Remove records at ages younger than first observation and older than age of censorship or transition.
Number of cases = 1287
Number of male person period records = 6710

Remove records with incomplete covariate information after imputation and lagging.
Final number of male partner cases = 1230
Final number of male person period records = 4701

Figure 2.1: Sample selection process.
The final stage of selection follows the application of imputation methods for missing covariate values. Unknown values are filled in using known measurements from neighbouring points, and covariate measures are lagged by one year. Following this, any records still containing missingness are deleted and the sample is comprised of complete cases only. This final sample, which will be analysed to address the first research question, consists of 1569 women and 6182 person-period records.

Addressing the second research question involves analysing data from only women with observed transitions. From the sample of 1569 women, there are 287 with a recorded employment exit, and only records relating to the age of transition are included in this second sample. Analysis for this research question involves comparing only the type, not timing, of the work exit and consequently records for ages prior to the age of transition are not included.

The third research question addresses employment transitions of the male partners of working women aged between 50 and 59. Initially, as shown in grey boxes in Figure 2.1, this sample is comprised of men from the 1569 households selected for the analysis of women’s transitions. This is further modified, however, with the removal of men who did not work during the time frame of interest; that is, when his female spouse was aged between 50 and 59. This removes 201 cases from the analysis, to give a sample of 1368 men.

The male spousal sample is refined again in a similar process to that followed for the female partner sample explained above. Only men observed on at least two consecutive waves, and that report as employed on at least the first of these, are included. A person-period dataset is constructed from this sample. It contains 1287 cases and one record for each year between the female spouse’s age of 50 and 59 inclusive. This results in 12870 person-period records.

Adjustments are then made to the male partner dataset so that records relating to periods prior to the age of first entry and after the age of censorship or transition are removed. The person period dataset at this point has 6710 entries for 1287 cases. Following this, missing covariate values are addressed by filling in with neighbouring known measurements, and are lagged by one year. Any remaining records with unknown values are removed. The final male partner sample is comprised of 1230 individuals and 4701 person period records.
2.2.2 The selected ELSA questions

The research questions of this thesis relate to women’s later life employment patterns and the individual, household and partner characteristics that influence them. Addressing these hypotheses requires information on sample member’s labour force status as well as data on demographics, health, income and wealth. The specific ELSA questions used in this analysis are described here, beginning with the employment measure and transition indicator. The descriptions of other selected questions are organised according to measurement level, with women’s and male partner individual attributes explained first and household characteristics following that. Transitions out of employment will be modelled using discrete time event history models, which will be formally specified in Section 2.3. A particular advantage of this methodology is that respondent’s health, income, wealth and other appropriate attributes can be incorporated as dynamic processes that may change in status or value over time. In these instances indicators are designated as time varying and data are used from each of the available ELSA waves where eligible sample members are aged between 50 and 59. Other measures, however, are considered fixed entities and assumed constant over time. These time invariant attributes, which include respondent’s level of education, social class and tenure, are assigned the value given on first entry into ELSA.

2.2.2.1 Measure of labour market position and transition indicator

Reported employment status is used in this research, in which participants are asked ‘Which one of these would you say best describes your current situation?’. Responses are selected from employed, self employed, retired, unemployed, permanently sick or disabled or looking after home and family. In this analysis the employment and self employment choices are amalgamated to form one common state of employment, with all other options collectively considered as non-employed states. A transition is defined as a change in status from employment to a non-working state; this is the dependent variable needed to address the first and third research questions.

The second research hypotheses relate to different types of transition with a distinction between involuntary and voluntary movements. The difference between involuntary and voluntary retirement is in the extent of personal choice an individual has on the timing of the
transition, with involuntary transitions likely arising from employment or health constraints (Radl and Himmelreicher, 2014). Identifying and classifying individuals into pathways can be achieved using a combination of reported labour market position and stated reasons for retirement (Radl and Himmelreicher, 2014). For analysis in this thesis a transition is designated as involuntary if a woman exits employment prior to state pension age and reports a not working, nor retired position of permanent illness, unemployment or caring; these are the labour market states likely to be entered when transitions result from job or health problems. A voluntary transition is designated where a woman identifies as retired. This classification is supported by ELSA data relating to reasons for retirement, as detailed in the following paragraph.

ELSA participants are asked to give reasons why they stopped work, and responses are available for 104 of the 287 women who have a recorded transition. Of these, 82 are allocated to the involuntary exit group and the remainder into the voluntary. Analysis of the available job history information shows that 37% of the involuntary exit women gave either their own ill health or that of a friend or family member as their reason for leaving work, whereas no participants who reported as retired gave these reasons. A further 37% of women designated as having an involuntary exit stated one of work stress, business closure, redundancy or dismissal as their reason from exit, compared to 9% of the voluntary exit group. The remaining 91% of voluntary exit women stated time with family, coordination of retirement timing with their partner, wanting to enjoy life, wanting a change or having been offered reasonable terms to retire early as their rationale for leaving. In contrast, these reasons account for only one quarter of the involuntary transitions. Women designated as having an involuntary exit, therefore, tend to cite reasons that reflect a low level of choice and control over timing. Those in the voluntary retirement group rarely identify these same events as the reason for their transition.

Given the above, the allocation into the voluntary and involuntary exit groups of the selected ELSA sample appears sufficiently accurate and justified. Note that the high level of missingness of the ELSA questions referred to (unknown responses for 183/287 cases, or 63.8%) will prevent them from being directly incorporated into the modelling process; they are used here to justify and provide support for decisions made during data preparation.
The grouping of women into these voluntary and involuntary transition categories facilitates a comparison of those who report as retired with those giving an alternative non-employed status. This comparison is necessary for determining whether there are differential retirement pathways for older women and the predictors of these pathways.

Literature presented in Chapter 1 describes women’s retirement as a complex process with periods of employment alternating with time out of the labour market (Loretto and Vickerstaff, 2013; Duberley et al., 2014). However of the 1569 women in the ELSA sample selected for this research, 1282 (81.7%) reported continual work between 50 and state pension age, 247 (15.7%) made a single transition out of work with no return and only 40, or 2.5%, transitioned and then subsequently returned to work. Eleven of these 40 women moved into retirement and then back to work, six re-entered employment from unemployment, whilst three transitioned back after a period of illness. Twenty reported an employed state after initially entering a period of caring for home or family. As proportions of the 1569 women sampled, 0.7% of women returned to work from retirement, 0.3% returned from unemployment, 0.2% from illness and 1.3% from a caring role.

The low proportion of recurrent transitions observed in the studied ELSA sample do not support claims that older women make repeated movements in to and out of the labour market. This may be a reflection of the granularity of data collected. ELSA questionnaires were administered on a minimum two yearly basis and this may not be often enough to observe periods of short term employment and casual work. With the sample figures as given, however, the proportion of recurrent transitions is too low to support the modelling of transitions following the first detected and work exit is, subsequently, treated as an absorbing state.

### 2.2.2.2 Measures of individual level attributes

Data on education and social class, income, health and dispositional effects are collected at the individual level in ELSA and within the couples sampled for this research each member has their own distinct allocated status or value. Note that a measure of age is not considered here; rather, it is included in Section 2.4 as part of a wider discussion on the measurement of time for this longitudinal analysis.
Education and social class

For the purposes of this research both an individual’s level of education and social class are regarded as time invariant. Educational attainment is measured as the highest qualification achieved by the date of a respondent’s first ELSA interview and sample members are classified into one of three groups. The highest level is for those with a qualification higher than A level or equivalent; this indicates post-secondary education. The middle group have obtained a secondary school level qualification, whilst those in the lowest category have not. Social class is also categorized into three occupational groups following the National Statistics Socio-economic Classification (NSSEC). The first group consists of higher managerial, administrative and professional occupations, whilst the second is comprised of intermediate workers, including those in positions that do not involve supervisory responsibilities. Routine and manual workers form the third category.

Income, working hours and employment history

The selected ELSA income measure is the gross weekly total of earnings from employment and self employment, private and state pension payments, benefits and any other sources. It is included as a time varying measure to account for any change in a respondent’s income during their observation window. ELSA also collects data on respondent’s working hours. Sample members are classified as working either part time if they work less than 35 hours per week, or full time otherwise. This boundary, of 35 hours, is that specified in the ELSA dataset and we follow that precedent here.

A measure of total time spent out of the work force prior to the age of 50 is constructed using past employment information from the life history module of ELSA. Job start and end dates are recorded for the period of time between sample members leaving full time education and administration of the questionnaire in 2007. The total number of years that each woman spent out of work is calculated using these dates. However incorporating this information into the event history model for women’s transitions is problematic in that life history data was only collected in wave 3 of ELSA, and thus it’s inclusion considerably decreases the number of complete cases available to analyse. Job start and end dates were available for 1056 of the 1569 women in the dataset - and the one third that are missing would
be removed completely from the analysis should the job history measure be incorporated. Imputing this information would require further detailed and complex use of the life history dataset, but missing data analysis of this nature is not the primary focus of this work. In Chapter 6 we concentrate on missing data issues arising from the application of longitudinal models given the particular sampling design of ELSA; the imputation of unknown values in historical measures falls outside the scope of this analysis. Additionally, the selected sample dataset is unlikely to support the inclusion of further information into what is an already complex modelling structure. For this reason, the association between career history and later life retirement timing is not considered further in this analysis.

**Health and caring**

Three measures relating to a person’s health are used in this research. The first, an indicator of long term health, is constructed from two ELSA questions. One asks respondents if they have a long standing illness, the second asks whether the illness is limiting and the combined information from these indicates the presence of a long term limiting illness. This variable is regarded as a measure of functional limitation associated with chronic conditions (Manor et al., 2001). A second measure indicates general self reported health with ELSA respondents selecting from options of excellent, very good, good, fair or poor. A ‘good or better’ category is formed by combining the first three of these, with the remaining two aggregated to signify poor health. Self rated health measures of this form are a valid indicator of overall assessment of health status - particularly among the elderly (Manor et al., 2001) - and provide a valid summary of more detailed mental and physical health measures (Bailis et al., 2003). The third health measure is of deterioration in a person’s condition and is indicated where there has been a decline in health status, either from having no limiting health condition to having such a limitation, or from good or better to poor self rated health. This is commensurate with the approach of Szinovacz and Deviney (2000), who include a similar measure of decline in their analysis of married couple’s retirement patterns. Each of the three health covariates - of a long term limiting illness, general self rated health and deterioration in health - is incorporated as a time varying measure.

A final individual level time varying characteristic, of caring responsibilities, is indicated
where ELSA participants stated that they had looked after someone in the last week. This may have been a spouse or partner, child, grandchild, parent, other relative or friend or neighbour.

Attitudinal effects

Attitudinal effects were raised in Chapter 1 as encompassing job satisfaction and job quality, with a ‘good’ job defined as one with adequate pay and training opportunities, a level of autonomy, security, a sense of achievement and opportunities for employees to apply their skills. The strength of a person’s marriage was also given as a likely influential factor with those in ‘high quality’ marriages expected to exit the workforce earlier than those in strained relationships (Szinovacz and Deviney, 2000). ELSA has twelve questions available that relate to the employment context; these items include an overall measure of job satisfaction as well as indicators that capture each of the above stated components of a good job. A measure of the quality of the person’s relationship is also included, with respondents asked to state whether they feel very close, quite close, not very close or not at all close to their spouse or partner.

Inclusion of the above job and marital quality variables in this analysis is, however, potentially problematic due to missingness. The employment context questions were not asked in wave 1 of ELSA and, along with the relationship items, were asked as part of the self completion module, but this has a lower response rate than other ELSA units. Response rates for the self completion, housing, and income and assets sections are detailed in the ELSA technical reports; in wave 1, rates were 92%, 99.6% and 99.9% respectively (Taylor et al., 2007, p. 30) whereas figures for wave 2 are 89.8%, 99.9% and 99.0% (Scholes et al., 2008, p. 36). The self completion response rate fell further again in wave 3, to 86.4%, whilst those for the other mentioned modules remained stable (Scholes et al., 2009, p. 53). Figures were unavailable for waves 4 and 5. Additional details in the cited technical reports show that employed persons are at higher risk of not responding to the self completion questionnaire compared to retired persons; this might further impact on the incidence of missingness in our selected ELSA sample as it contains only employed women. We can therefore expect a higher rate of missingness within the job context and marital relationship variables for each
Ideally, the attitudinal variables considered here would be structured as time varying constructs; it is reasonable to assume that job satisfaction, closeness of the marital relationship and other associated measures are not fixed, but change over time. However 278 of the sampled 1569 women - that is 18% - have no response for these items. If these variables were included, but only complete cases analysed, then the sample would reduce to 1291 women and the number of observed transitions would fall from 287 to 197. This is a 31% decrease in the sample transition rate. Imputing missing attitudinal variables is not a viable option as the majority of sample members that have unknown values for these variables tend to have them for all other attitudinal measures. This means that for these participants there are no recorded observations for some aspects of job quality and satisfaction, for example, that could be used to impute those that are unknown. Unobserved elements of these variables would need to be imputed from a wider set of known indicators, but applying multiple imputation methods may be prohibitive where there is a high incidence of missingness across the sample dataset. The details of the limitations of multiple imputation in this research are discussed in depth in Chapter 6.

An alternative approach for the attitudinal variables is to structure them as time invariant and use respondents’ baseline values for the relevant indicators. This means that women need only one observation for each covariate and, where women are observed on multiple occasions, the earliest is taken as the baseline value. When this was done for our ELSA sample the number of included households reduced by 103 (7%) and observed transitions by 51 (18%). The limitation of this approach, however, lies in the feasibility of the assumptions made. Constructing job quality and relationship attributes as time invariant implies that they do not change over a time span that is up to ten years long - this is a lengthy period throughout which marital quality, job satisfaction and other associated measures are assumed constant. This is not considered a realistic option to pursue; it is reasonable to expect these particular attitudinal attributes to be more volatile with more frequent changes in value over time than what this time invariant structure assumes.

The difficulties outlined here of incorporating the relationship quality and employment context variables exemplifies a wider issue of appropriate methods for addressing missing-
ness in attitudinal variables within longitudinal studies. Minimising missingness by structuring as time invariant rather than as time varying might be feasible for some measures - for example wealth quintile group, which is likely to be more stable over time - but is less desirable where a greater degree of change in the given measure could be expected. Whether or not imputation methods are viable for more volatile measures depends on the specific structure of time units and dispersion of missingness throughout the analysed dataset; it is the length and size of the time metric in any longitudinal study that determines this. In the context of this research, we are using a ten year axis structured in one yearly units and that, as will be detailed in Chapter 6, contributes to the infeasibility of multiple imputation methods as it increases the scarcity of known data across the dataset compared to, for example, a ten year axis scaled in two yearly units.

As outlined here, including job and marital quality variables increases the incidence of missingness in the analysed dataset. Deleting cases with unobserved values removes an unacceptably high number of women from the sample, imputation is not feasible and structuring as time invariant requires questionable assumptions to be made. Given this, it is not viable to include the study of the attitudinal and dispositional effects in this analysis and they are not considered further.

### 2.2.2.3 Measures of household attributes

Tenure, the presence of a child in the household, pension wealth and non pension wealth are the household level characteristics included in this research. Both the female and male partners within any given household are allocated the same value of these attributes.

**Tenure and presence of children**

ELSA respondents are asked whether they own their home outright, have bought it with the help of a mortgage or loan, have shared ownership in which they pay part rent and part mortgage, rent or live rent free. For the purposes of this research these responses are categorised into three tenure states of own outright, has a mortgage component or renting. For the presence of children, the convention established in ELSA is followed; a dependent child is defined as a resident aged 17 or under who earns less than £5000 per year (Institute
The proportion of cases that show a change in housing status or number of children present is relatively low. Of the 1569 women sampled less than 10% had a recorded change from their baseline level for either of these measures. To give some comparative figures, 16% of the observed sample experienced a change in self rated health status and 22% in limiting health. This lower rate of change in the tenure and presence of child measures may, to an extent, be caused by the majority of sample members being observed for less than four or five consecutive waves. Women who responded on only two or three occasions have shortened observation windows, and health may be more variable across short time frames than housing status or the number of resident dependent children.

Hosmer et al. (2008) raise the potential to overfit survival models when incorporating time dependent predictors and assert the need for strong evidence to support their inclusion. Given the relatively lower rates of change in observed tenure and dependent child states, the decision is taken to configure these measures as time invariant with sample members allocated the status that was recorded at the time of first entry into ELSA. When structured as time invariant the composition of the risk set for each tenure or child dependence group remains static throughout the studied age range. Estimated coefficients from the fitted event history model will give the risk differential in every time period between age 50 and 59.

**Pension and non pension wealth**

ELSA is unique in that it contains detailed measures of individual and household financial circumstances, including pensions. The selected measure of pension wealth is the total of a couple’s accumulated wealth from state and private pension sources at the time of their ELSA interview. This value is, for each individual member of the couple, the pension entitlement that they have if they were to retire at that point and accumulate no further rights. The state pension component includes accumulated rights to the first tier basic state pension and the second tier earnings related pension. Private pension wealth includes that from defined benefit and defined contribution schemes that respondents are currently a member of, as well as entitlement from schemes previously joined but no longer contributed to. Non pension wealth is the total of a couple’s savings, investments, housing and physical wealth net of
any financial or housing debt. Pension wealth and non pension wealth are both regarded as time varying measures that reflect changing values over time; further details relating to the operationalization of these measures and the form that they take in the later modelling process are given in Section 2.6.3.1.

2.3 Modelling approach and strategy

Addressing the first and third research questions of this thesis involves determining whether male partner’s health and employment status and household pension wealth are statistically significant predictors of women’s labour market exit, and if so evaluating the magnitude of any effect. The second research question concerns the differential impact of pension wealth, women’s health and male partner’s health across voluntary and involuntary exit pathways and requires testing these attributes for significance once destination state is taken into account. The analytic approach used to achieve these aims is presented here; in Section 2.3.1 the event history model for transitions out of employment is specified and in Section 2.3.2, the logistic regression model for the different pathways is detailed.

Survey weights are not used in the analysis detailed in the following sections. Weighting is appropriate when the aim is to estimate population descriptive statistics from a sample that is not representative of the target population (Solon et al., 2015); it is not advised where the objective is to estimate causal effects from regression models (Aitkin et al., 2009; Allison, 2010). Weights included in survey datasets may not fully correct for attrition and non response related to the response variable of interest (Pyy Martikainen, 2013), with the use of weights to adjust for attrition in some event history applications showing limited impact on model estimates (Hill, 1997). As an alternative to weighting, a recommended approach is to include available data from attriters in the analysis (Pyy Martikainen, 2013). That is the strategy followed in this research, with included data limited to that from consecutively observed waves as necessary for event history analysis. Models are fitted using R software version 3.2.2, package lme4.
2.3.1 Modelling the incidence and timing of women’s and male partners’ employment exit

A multilevel framework captures the complexity of the retirement process (Szinovacz, 2012) and is realized here with the fitting of a hierarchical discrete time event history model. Steele (2011, p. 10) presents the general form of this model and it is adapted in Equation 2.1 to reflect a two level structure. Repeated observations of time varying measures are positioned at the lower level and time invariant characteristics on the higher level. A cloglog link function is used, in recognition of the underlying continuous time process being studied; whereas transitions out of work take place in continuous time, only the year of exit is considered in this analysis. The cloglog link is recommended in such cases where time has been discretized, because the associated model assumptions and parameter estimates are consistent with those for a continuous time specification (Allison, 1982; Singer and Willett, 2003). This model can account for women with an observation window that ends prior to transition, with such censored cases contributing minimum known employment durations in which no event has occurred.

\[
\log(\log(1 - p_{it})) = \alpha^T z_{it} + \beta^T x_{it} + u_i
\]

(2.1)

The outcome of this model is the transformed conditional probability, or hazard, that a transition occurs at age \( t \) for individual \( i \) (denoted by \( p_{it} \)). The vector \( \alpha \) is a parameter vector and \( z_{it} \) a vector of time functions. Together these vectors represent a duration effect and are referred to as the baseline hazard function. The explanatory variables that may impact on the likelihood of a transition occurring are denoted by \( x_{it} \) with the elements of \( \beta \) being parameters that quantify their influence. This structure permits time varying covariates - which in this study are lagged by one observation period - and interaction terms between \( z_{it} \) and \( x_{it} \) allow non-proportional covariate effects. The inclusion of \( u_i \) in the model accounts for unobserved individual level time invariant characteristics.

Model fit is assessed using the log likelihood ratio test. This evaluates whether additional information - in the form of added parameters - sufficiently improve model fit so as to be con-
sidered statistically significant. This method is preferable to the alternative Wald approach; the two tests are asymptotically equivalent, but can give conflicting results in finite samples. The likelihood ratio test is considered the more reliable and recommended option (Pawitan, 2000; Fox, 2008; Agresti, 2013) and is consequently used throughout the modelling process in this research. A 5% threshold is used to assess significance.

The model expressed in Equation 2.1 is estimated separately for each of women’s transitions and those of the male partners and in both cases, the domestic context is incorporated through household and partner level covariates. However this method might be considered limited in scope, because it involves analysing separately the transition of each partner within a couple; employment pathways of couple members are not modelled jointly. A model that does predict the transitions of both spouses within each couple would also provide a representation of the household structure in terms of covariates, but could additionally take into account any correlation between outcomes of the partners. De Preter et al. (2015) adopt this strategy in their analysis of couple’s retirement in eleven European countries, using data from the Survey for Health, Ageing and Retirement in Europe (SHARE). However, despite it’s advantages, fitting such a multilevel model has two limiting consequences: if applied to this research, it would restrict the analysis with regards to both age and partner’s employment status in ways that are described below.

Considering the age issue first, a discrete time event history model requires all observations to be placed along a common time axis. In this case, there are three options of age, calendar time and year on study; later in Section 2.4 we give a more detailed consideration of these options, but for now the pertinent point is that the employment pathways of the selected ELSA sample are measured along an age axis that ranges from 50 to 59. To incorporate men’s trajectories into the same model would require either the sample to be restricted to couples where both partners are aged between 50 and 59, or to extend the age axis to whatever the age range of the male partners is. In the selected sample the youngest male partner is 31 and the oldest 87 - this is prohibitively wide.

Jointly modelling men’s and women’s outcomes would restrict the sample with regards to men’s labour market status. Men’s transitions would be incorporated only if they were exiting from an employed state, as the female partners are. This would limit the sample
to households in which both partners were in employment which, if the aim is to consider women’s retirement across a range of different domestic contexts, is counterproductive as it would exclude from the analysis any couple in which the male member is not working. Taking this approach would be appropriate should the focus be the incidence of joint retirement, rather than the impact that differing spousal or partner labour market states and other attributes might have on women’s employment.

To position this analysis of older women’s transitions alongside that of their partners and model transitions jointly would, therefore, necessitate an intractable structure for time and a more constrained sample. The decision to model couple’s transitions separately is seen elsewhere in the literature; see Szinovacz and Deviney (2000) for one. The modelling process and subsequent results for the women’s transitions are explained in Chapter 3, whilst those for the male partners are in Chapter 5.

The event history model of Equation 2.1 is fitted under a conditional likelihood assumption. This is a consequence of the sampling strategy in that women are selected from ELSA if they were aged between 50 and 59 when first observed - this results in a truncated or ‘delayed entry’ sample, in which participants are not all observed from the same single time point. Fitting discrete time event history models to a truncated sample requires adopting a conditional likelihood framework (Guo, 1993). In such an approach it is assumed that the first event that is observed is the first to have occurred; in this context, we assume that women have remained in constant employment from the age of 50 until either the time of any observed exit from work or the end of their observation window. There are two alternative methods for analysing the employment pathways that do not require making this assumption. The first is to analyse only participants who have been observed for all five waves of ELSA, and the second is to use an alternative time axis other than age and configure employment trajectories along a ‘time on study’ axis. The viability of these options are considered in more depth in Chapter 6. For the event history models fitted in Chapters 3 and 5, the conditional assumption applies.
2.3.2 Modelling the destination state and subsequent pathway

The multilevel discrete time event history model specified in Equation 2.1 predicts the conditional probability that an older woman leaves work prior to state pension age. That particular model provides the necessary information to answer the first and third research questions which relate to the timing of labour market exit and explanatory reasons for it; partner’s health, partner’s employment status and household pension wealth are of particular interest. The second research question asks whether these measures also influence the pathway that a woman is most likely to follow after any transition that occurs. We consider two exit trajectories distinguished by women’s reported post-transition labour market status. One is characterized by women that self report as retired after leaving work, despite having transitioned prior to the state pension age of 60. The second pathway is typified by exits into caring, unemployment or illness states. The two pathways are designated as voluntary and involuntary respectively; transitions into caring, unemployment or illness are considered the result of an involuntary event such as job loss, poor health of the respondent or need to provide care for a family member. Reported retirement prior to state pension age, however, is regarded as a voluntary event that may be associated with adequate financial resources rather than forced exit.

Possible modelling approaches that can account for these two different destination states are summarized by Allison (1982). One option is to modify the event history model given in Equation 2.1 to account for the type of transition that occurs, and fit a multinomial logit model based on three outcomes of continued employment, retirement and the alternative amalgamated states of caring, illness and unemployment. However the accuracy of any estimates and conclusions from any model is dependent upon the available number of observations with which to fit each type. In a multinomial specification the sample of 287 transitioned women would need to be divided into two subgroups; the first would comprise of 134 women who report as retired, whilst the remaining 153 form the second alternative group. Employment trajectories of women in each of these categories would then be compared to those of the 1282 women who did not exit. Estimates of the effects of the covariates of interest for each destination state, therefore, will be based on a significantly reduced number of events. This can result in a considerable loss of statistical power (Allison, 1982) and
imprecise estimates of effect sizes. Some analysis relating to this issue was conducted for this research, but due to space restrictions is not reproduced here; results did, however, confirm that the selected ELSA households have insufficient observed transitions to support the fitting of a multinomial model.

Allison (2010) provides an alternative modelling strategy. When different types of event ‘represent alternative means for achieving a single goal’ Allison advocates a two stage conditional method in which an event history model for the timing of labour force exit is constructed first, where no distinction is made between women with respect to destination state. The sample is then restricted to women who transitioned out of work and a binary logistic model for destination state is fitted to this data. In the context of this thesis, the alternative options of transitioning into retirement and exiting into a non-retired state both result in women detaching from the labour market and the two stage modelling approach is therefore an appropriate one to use here. The first required model for the timing of labour force exit is that specified as Equation 2.1 in the previous section; results from this will address the first research question. For the second research hypothesis only the sample of transitioned women is analysed with the fitting of a binary logit model comparing exit into reported retirement prior to state pension age with transitions into alternative non-working states. This model is formally specified in Equation 2.2. The dependent variable is the log odds of an individual \( i \) experiencing an involuntary transition into a state of either caring, unemployment or illness relative to voluntary exit into early retirement. The vector \( \beta \) contains individual, household and partner level explanatory variables. The process of fitting this model and subsequent results are detailed in Chapter 4.

\[
\text{logit}\left(\frac{p_i}{1-p_i}\right) = \alpha + \beta^T x_i
\]  

(2.2)

Note that the second research question of this thesis relates to older women’s transitions out of work and consequently the model specified in Equation 2.2 is fitted only to the sample of transitioned females; modelling of voluntary and involuntary transitions is not extended to the male partners of the studied households. The event history model and the binary logistic model together form a conditional logit approach and from this, we can obtain a more comprehensive picture of older women’s employment trajectories in the ten years prior
to state pension age. Replicating the full two-stage analysis for the male partners, however, would not provide the equivalent information. The male partners range in age from 31 to 87, and thus further analysis of their labour market behaviour after any transition that is made would not provide any meaningful depiction of employment or retirement trajectories; the male partner sample captures men who are at a variety of career stages and labour force states and is not focused on specific pre-retirement years. The analysis of male partners in this thesis is limited to the occurrence and timing of their transitions out of work and is expected to further understanding of the domestic context in which the female partner employment pathways are positioned, rather than provide a comprehensive picture of their own labour force trajectories.

2.4 Measuring time and employment events

The first stage in fitting the discrete time event history model specified in Equation 2.1 is to establish the relationship between the probability that a transition occurs and time; that is, to estimate the baseline hazard function. This requires the construction of a time axis along which employment trajectories can be placed, as well as a formal definition of what a transition is and how one is detected in the observed data. The measurement of time and definitions for key employment events are detailed in this section.

2.4.1 Structure of the time axis

It was stated in Section 2.3, in the presentation of the event history model, that for this analysis time is measured in terms of age rather than either alternative option of calendar year or time on study. The justification for this choice comes from the theoretical framework of Chapter 1, where retirement was portrayed as a dynamic process that evolves over time. It is argued that the way in which retirement develops is more likely to depend upon a woman’s age than what year it is or how many ELSA questionnaires have been filled in. Age is the logical choice for the metric of time, but in Chapter 6 we return to this issue and consider in depth the viability and any advantages of the alternative options. Whilst age is used here other metrics are used elsewhere in the retirement literature (Blau and Riphahn, 1999;

AGE INFORMATION FOR ELSA PARTICIPANTS IS RECORDED TO THE YEAR LEVEL ONLY AND THE TIME AXIS WILL SUBSEQUENTLY BEGIN AT 50 AND END AT 59. HOWEVER NOT ALL WOMEN ENTER THE ELSA STUDY AT AGE 50 AND THIS ‘DELAYED ENTRY’ ISSUE HAS IMPLICATIONS FOR THE MODELLING PROCESS; THESE WERE EXPLAINED BRIEFLY IN SECTION 2.3.1 AND WILL BE DETAILED FURTHER IN CHAPTER 6. THE PERTINENT POINT AT THIS STAGE IS THAT THE EMPLOYMENT TRAJECTORIES OF THE SAMPLED WOMEN HAVE NO COMMON START TIME AND THIS LEADS TO DIFFERING OBSERVATION PATTERNS FOR THE RESPONDENTS. THE AGE DISTRIBUTION OF THE WOMEN IN THE SAMPLED HOUSEHOLDS IS SHOWN IN THE TOP GRAPH OF FIGURE 2.2. JUST OVER ONE THIRD (34.6%) OF WOMEN WERE OBSERVED FROM THE AGES OF 50/51, 26.6% JOINED AT 52/53 AND 5.6% AT THE OLDEST AGES OF 58/59. NO AGE RESTRICTIONS WERE PLACED ON THE MALE PARTNERS, AND THEIR AGE DISTRIBUTION ON ENTRY IS SHOWN IN THE LOWER GRAPH OF FIGURE 2.2. THE AGE OF FIRST OBSERVATION FOR THESE MEN HAS A RANGE OF 56 YEARS, FROM AGE 31 TO 87.

![Figure 2.2: Age distribution at baseline for women and male partners](image)

Variation in women’s age of entry, when combined with the biennial data collection schedule of ELSA, causes differing observation patterns amongst women in the complete cases sample. Approximately one third of the 1569 women are observed on some or all of the ‘even ages’ of 50, 52, 54, 56 or 58; another third responded at the ‘odd’ years of 51, 53,
55, 57 or 59 and the remaining have irregular patterns that do not fit either of these. The difficulty arises, then, from the need to project all women’s employment trajectories on to one common time axis irrespective of which observation pattern they follow.

The decision is made to use yearly units of age for the modelled trajectories as this will afford a more detailed analysis of women’s retirement pathways than what could be achieved with a two yearly or wider interval structure. The yearly axis also ensures that data of women first observed as employed in ELSA at age 58 are included in the analysis, with any transition recorded at 59. In a two yearly age structure these transitions could not be studied. However with a one year scale there are consequential issues relating to periods in which women haven’t been observed; these relate primarily to unknown covariate measures and this is addressed in Section 2.6 when the configuration of predictors is discussed. Relevant at this point is that a time axis is established, that begins at age 50 and progresses in yearly units until 59.

As explained earlier in Section 2.3 separate event history models will be fitted for the employment transitions of women and the male partners. However the wide range of male partner ages - from 31 to 87 - means that a one yearly axis is infeasible in models for male partner transitions. A grouped interval axis would be an alternative, with interval widths of ten years; however, given that the primary aim of this thesis is to examine the influence of the domestic context on women’s retirement pathways, a more informative approach is to model the employment pathways of the male spouses relative to the female partner’s age. This configuration will emphasise the events that occur in the male partner trajectories as the female partner approaches state pension age. Further details of this approach are given in Chapter 5 where the modelling of the male partner trajectories is discussed in depth.

2.4.2 Defining key employment events

In this research a woman’s labour market position is given by her self reported status at the time of each ELSA response. The possible options are employment and the non-working states of retired, long term illness, caring for home and family or unemployment. An observed employment trajectory begins from the age of the respondent’s first ELSA interview, and is formed from a sequence of observed labour market states. Trajectories can end ei-
ther in censorship or with a transition. Censored women are defined as those who remain in employment until either age 59 or they leave the study, and their age of censorship is taken as the age of the last recorded interview. Of the 1569 women in the complete cases sample 1282 are designated as censored.

A transition is identified by a change in a respondent’s self described status from employed to either retired, illness, caring or unemployed on their next interview date. In the women’s sample of 1569 households 287 such events are observed, giving a transition rate of 18.3%. The age at which any employment exit occurs is determined either through job history information collected in ELSA or by assumption. For 167 (58%) of the transitioned women the month and year that their job ended is available and their transition age is determined from this, and rounded to year level; for the remaining 120 the age of exit needs to be assumed and is taken to be one year older than the age at which the last ‘employed’ response was given.

2.5 Missing data

Missingness in the observed employment sequences can occur either between the age of 50 and entry into the study for delayed entry cases, between the final included observation and age 59 when right censored, or within the observation window. In this section each type of missingness is discussed in turn.

2.5.1 Delayed entry

Women entering ELSA at different ages cause sequences to be truncated at the beginning, with first measurements only recorded after the age of 50. The discrete time event history models fitted to this delayed entry sample are constructed under a conditional likelihood framework, in which it is assumed that the first transition observed is the first that has occurred (Guo, 1993). Alternative methods for dealing with this type of sample include analysing only women who have been observed from the age of 50, imputing unobserved employment states, or reconfiguring the time scale used so that missingness does not occur at the beginning of the observed trajectories.
Research based on cases observed from the same age is common in retirement literature (Drobnič, 2002; Radl and Himmelreicher, 2014; Madero-Cabib et al., 2016). However, restricting the ELSA sample in this way would significantly decrease the number of women studied; only 15% of the analysed sample were interviewed at 50 with 21% at 51. Given this, late entry women are included in this analysis and trajectories are modelled under the conditional likelihood assumption. In Chapter 6, however, the alternative imputation option is considered in depth. The viability of different forms of time axes, and consequences of not including delayed entry cases, are further discussed in Section 6.3.

### 2.5.2 Censorship

Women are followed in this analysis until the point that they either transition out of work, reach the maximum age of 59 or no longer participate in ELSA. Event history models can accommodate such observations with women contributing minimum known survival times in which they have not experienced the event of interest; these women are known to have remained in work until at least the age of censorship and they therefore contribute to the risk set up until this point. Missingness of this type is sufficiently addressed in the modelling approach and therefore not considered further.

### 2.5.3 Missingness within the observation window

In addition to missing observations at the beginning and end of the studied age range, women are also not observed at every year of age in between their first and last recorded interviews. Sample members can be arranged into one of three groups depending on their particular sequence of observed and missing values. The first two groups are comprised of women who have followed a regular two-year interview schedule, but are differentiated according to the woman’s age when first observed. Participants who were first interviewed at either 50, 52, 54, 56 or 58 and every two years from then until exit have what is termed an ‘even’ pattern of observations, with missing data at the ‘odd’ ages of 51, 53, 55, 57 and 59. Approximately 36% of the sample followed this pattern. The second group of women were first observed at an odd age and have sequences of known values at odd ages, but no available data for years in between. One third of respondents had this type of sequence. The third group is
comprised of women with more erratic response times that follow neither of these alternating arrangements. Thirty percent of sample respondents had such a random sequence.

The alternating patterns of observation times cause complications for analysis in that covariate measurements are missing for every second time point. They are, however, available at adjacent younger and older ages and these values that have been observed can be used to inform the unobserved and missing. Using a modified ‘last value carried forward’ approach, ages are grouped into intervals of two years and variables are assumed to have the same value for each of these two years. Any unknown measurement, therefore, are allocated the value of the known observation. If no observation is made at age 51, for example, then values taken at 50 are assumed to hold also at 51 and vice versa. This method deals with missingness for women following a regular odd or even pattern in which an unknown value occurs adjacent to a known observation. There are, however, two situations where missing data are present that this method does not address.

The first of these instances applies to the women with erratic observation patterns that do not follow regular two year intervals. This situation arises when ELSA questionnaires are administered in consecutive waves, but not necessarily exactly two years apart. A sample member, for example, could first respond at age 50 in wave 1, but have her next observation at age 51, if her questionnaire in wave 2 is completed less than two years after the first. There could then be a longer age gap to the wave 3 observation, contributing to missing data in her record. Missing data in this situation will be characterised by unknown values for all time varying covariates, and will occur within the observation window at adjacent time points, because there is no known value at odd to inform that at even and vice versa. A second scenario that the above method did not address occurs when women follow regular two yearly observation patterns, but fail to respond to all aspects of the ELSA questionnaire. In these cases women have partial records at certain ages with some covariate measures available, but others missing. Missingness in this situation will again occur at consecutive ages, but only for a subset, rather than all, of the covariates.

In order for the analysis of women’s and partner transitions to proceed any records from the original sample of 2238 households with unknown values in at least one covariate measure were removed from the dataset, and models fitted to respondents with fully observed
records. As a result of this move to complete cases the original dataset, which consisted of 8698 person period records, was reduced to 6182 records and 1569 women. Of the women with deleted observations, some were still represented in the dataset with records taken at other time points. This means, therefore, that there are two possible sources of information from which unknown values for these cases can be estimated - records of other women who were observed at the same time as the unknown values of interest, and records that belong to the same woman but that were taken at earlier or later time points. The next stage in this discussion involves a more detailed look at the observations that were deleted in the move to complete cases only. We look at the source and amount of information that is retained in the sample from which unknown values could be estimated. With this the focus moves away from how missingness occurs over time to how it is distributed across the covariates of interest.

2.5.3.1 The distribution of missingness across covariates

Figure 2.3 shows how missingness in the original sample is distributed across the time varying covariates of interest. The bar graph on the left hand side plots the proportion of the person period records that have unknown values for each of the given predictors. The pension wealth measure has the greatest incidence of missing values with 1601 entries having no recorded value. This is 18% of the person period records affecting 37% of women in the sample. Measures of partner attributes are the next most likely to have missing values. The frequency of missingness in partner health and employment status are similar; in each case the value is unknown for 27% of women and approximately 16% of the person period records. Partner income is not recorded for 31% of couples and is missing in 12% of the person period dataset.

The right hand plot in Figure 2.3 shows how missingness is distributed across combinations of various time varying covariates. In this diagram grey represents unobserved data and white signifies known measurements, and the figures on the right hand side indicate the number of times that each combination appears in the dataset. The two particular patterns of missing data discussed earlier - where respondents have either fully missing or partially observed records - are identifiable in this graph. There are 559 instances where all covariate
values are missing and this is shown by the solid grey row in Figure 2.3. These are discussed further in the next section. Rows containing both white and grey regions depict partially missing records. There are 21 different combinations and more detail relating to these is given in Section 2.5.3.1.

**Fully missing covariate values**

The most common pattern of missingness in the person period dataset occurs when women have no recorded values for individual level, partner or household time varying predictors, and this is most likely to occur amongst women with irregular observation patterns. There are 268 respondents affected with a total of 559 person period records that are missing all of these measures. Table 2.1 details further the number of women and number of missing records. The top two rows show that 44 women had one record with no known measure-
ments; 187 women had two records and so on, with only one or two respondents having six or seven records of this type. These findings are consistent with the assertion earlier that the method of using adjacent known observations to estimate those unknown would not remove all missingness - it was stated that missing data would still be present amongst women with irregular response patterns and this would occur at adjacent ages. The high number of women with two records still containing missing values suggest this is the case.

Table 2.1: Distribution of removed records among women with missing individual, household and partner measurements

<table>
<thead>
<tr>
<th>Number of records with missing data</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of women affected</td>
<td>44</td>
<td>187</td>
<td>15</td>
<td>18</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Number of complete records</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>Number of women affected</td>
<td>0</td>
<td>52</td>
<td>57</td>
<td>38</td>
<td>69</td>
<td>28</td>
<td>23</td>
<td>1</td>
</tr>
</tbody>
</table>

These 559 records containing only missing values for time varying measures were deleted from the dataset prior to the fitting of the event history models. However in every instance the 268 women affected are still represented in the sample - no household with this type of missingness has been completely removed as a result of moving to complete cases. Whilst these women have records missing for some time periods they retain entries at other ages and consequently some measurements of individual, household and partner covariates are available that could be used to inform those missing. The bottom two rows in Table 2.1 show that each woman retains between two and eight records available that contain full information.

**Partially missing records**

Rows that contain both white and grey regions in the combinations graph of Figure 2.3 typify records that are partially observed. A grey area indicates the covariates for which values are missing whereas white represents those known, and there are 1431 of these records in the original dataset. Unknown partner measurements are a common form of missingness amongst these women with 855 of these partially observed records having no known values for both of spouse’s health and employment status. It’s likely that the high rate of unknown information in the pension wealth measure also stems from missing partner data; this was a
household measure of the total wealth held by both couple members and will be designated as missing if either the woman or partner’s pension resources are unknown.

This scenario of missing male spousal data likely arises when partners are not observed at the same time as the female household member. There are, in total for the entire original woman’s person period dataset, 477 households without partner health and employment status. Of these couples 81 have no recorded responses from the male member in any ELSA wave, and in the remaining 396 measurements are available, but are possibly recorded for time periods outside of the woman’s studied age range. Whilst there are partner values available from which missing observations could be estimated for these households, this would involve using measurements taken at least two years before or after the time point of interest.

2.6 Characteristics of the sample

So far in this chapter we have detailed the ELSA dataset, the selected sample and relevant questionnaire items and explained the modelling strategy. The metric for time that underpins this longitudinal analysis was established and the event of interest - a transition out of employment - has been defined. The incidence and distribution of missing observations has also been detailed. In this section further details about the sampled households are presented. First the distribution of transition rates for women at each year of age between 50 and 59 is described, along with rates for the male partners. Following that, the number and proportion of women and male partners with each of the individual and household level attributes of interest are detailed.

2.6.1 Observed sample transition rates by age

Table 2.2 shows sample transition rates for women and the male partners when the female couple member is aged between 51 and 59. As noted earlier not all couples are analysed for the male partner transitions; 1569 couples are included in the women’s sample, but due to missingness in men’s covariate values this is reduced to 1230 couples for the male partner analysis. The women’s transition rate shows an increasing trend over time and indicates that women are more likely to leave work as they approach their state pension age of 60. The
lowest observed rate occurs amongst 53 year old women with 2.1% having left work at this age; the highest rate of exit occurs at age 59 with 9.0% of respondents transitioning then. As these women grow older the probability of the male partner leaving work increases from 1.8% for women aged 51 to 4.6% for women aged 59. This is not a linear pattern, however, with the probability of the male partner leaving work highest, at 5.2%, when the female member is aged 54.

Table 2.2: Sample transition rate for each year of women’s age

<table>
<thead>
<tr>
<th>Sample statistics</th>
<th>Age 51</th>
<th>Age 52</th>
<th>Age 53</th>
<th>Age 54</th>
<th>Age 55</th>
<th>Age 56</th>
<th>Age 57</th>
<th>Age 58</th>
<th>Age 59</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of women of this age</td>
<td>543</td>
<td>643</td>
<td>758</td>
<td>760</td>
<td>806</td>
<td>774</td>
<td>754</td>
<td>668</td>
<td>476</td>
</tr>
<tr>
<td>Number of women’s transitions</td>
<td>18</td>
<td>16</td>
<td>16</td>
<td>30</td>
<td>32</td>
<td>36</td>
<td>44</td>
<td>52</td>
<td>43</td>
</tr>
<tr>
<td>Women’s transition rate (%)</td>
<td>3.3</td>
<td>2.5</td>
<td>2.1</td>
<td>3.9</td>
<td>4.0</td>
<td>4.7</td>
<td>5.8</td>
<td>7.8</td>
<td>9.0</td>
</tr>
<tr>
<td>Number of men partnered to women of this age</td>
<td>455</td>
<td>539</td>
<td>616</td>
<td>617</td>
<td>608</td>
<td>567</td>
<td>530</td>
<td>463</td>
<td>306</td>
</tr>
<tr>
<td>Number of male partner transitions</td>
<td>8</td>
<td>19</td>
<td>15</td>
<td>32</td>
<td>22</td>
<td>28</td>
<td>20</td>
<td>23</td>
<td>14</td>
</tr>
<tr>
<td>Male partner transition rate (%)</td>
<td>1.8</td>
<td>3.5</td>
<td>2.4</td>
<td>5.2</td>
<td>3.6</td>
<td>4.9</td>
<td>3.8</td>
<td>5.0</td>
<td>4.6</td>
</tr>
</tbody>
</table>

These sample rates form the basis of subsequent analysis that will address the set research questions. The figures in Table 2.2 show the transition rate for all women and male partners irrespective of their individual attributes and domestic arrangements; analysis relating to the first and third hypotheses will determine whether women coupled to men with health conditions or varying employment circumstances have transition rates that are significantly different from these. We also consider whether varying levels of household pension wealth are associated with significantly higher or lower transition rates than those given.

2.6.2 Women’s and male partners’ individual level attributes

Health issues, social class, educational background and working patterns are expected to influence the employment trajectories of both women and the male partners in this study, whereas caring responsibilities are expected to have a greater impact on women’s pathways. Table 2.3 contains the number of respondents and percentage of the sample that have each of the given attributes. Note that these are figures calculated from responses at the time of the couple’s first ELSA interview. These are not figures that the eventual fitted models will
be based on; the aim here is to provide baseline information about the characteristics of the sampled women and their spouses rather than detail figures relating to the later modelling process. The event history models will be fitted to a restructured dataset in which respondents have one record for each year of age that they are observed, and statistics that are relevant to these datasets are presented separately in the appropriate chapter - for women’s transitions, this is Chapter 3, for destination state analysis it is Chapter 4 and for male partner trajectories, Chapter 5.

Table 2.3: Observed statistics for women’s and male partner samples at time of first ELSA response

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
<th>Women</th>
<th>Male partners</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>%</td>
<td>n</td>
</tr>
<tr>
<td>Limiting health</td>
<td>No</td>
<td>1331</td>
<td>84.8</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>238</td>
<td>15.2</td>
</tr>
<tr>
<td>Self reported health</td>
<td>Good, very good, excellent</td>
<td>1460</td>
<td>93.0</td>
</tr>
<tr>
<td></td>
<td>Fair, poor</td>
<td>109</td>
<td>7.0</td>
</tr>
<tr>
<td>Caring responsibilities</td>
<td>No</td>
<td>1272</td>
<td>81.1</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>297</td>
<td>18.9</td>
</tr>
<tr>
<td>Working hours</td>
<td>Full time</td>
<td>703</td>
<td>44.8</td>
</tr>
<tr>
<td></td>
<td>Part time</td>
<td>866</td>
<td>55.2</td>
</tr>
<tr>
<td>Partner’s employment</td>
<td>Employed</td>
<td>1318</td>
<td>84.0</td>
</tr>
<tr>
<td></td>
<td>Retired</td>
<td>150</td>
<td>9.6</td>
</tr>
<tr>
<td></td>
<td>Illness, unemployed, caring</td>
<td>101</td>
<td>6.4</td>
</tr>
<tr>
<td>Social class</td>
<td>Managerial/professional</td>
<td>581</td>
<td>37.0</td>
</tr>
<tr>
<td></td>
<td>Intermediate</td>
<td>451</td>
<td>28.7</td>
</tr>
<tr>
<td></td>
<td>Routine/manual</td>
<td>537</td>
<td>34.2</td>
</tr>
<tr>
<td>Education</td>
<td>Less than O level equivalent</td>
<td>509</td>
<td>32.4</td>
</tr>
<tr>
<td></td>
<td>O level equivalent</td>
<td>574</td>
<td>36.6</td>
</tr>
<tr>
<td></td>
<td>Higher than A level equivalent</td>
<td>486</td>
<td>31.0</td>
</tr>
</tbody>
</table>

**Health and caring variables**

Health is represented in this analysis in three ways. The first assesses a respondent’s long term health status; persons are categorised into one of two groups depending on whether they report having a long term limiting illness. Amongst the studied women 238 (15.2%) reported having such a limitation, with a similar incidence (15.5%) also observed amongst the male
partners. For each gender this information is incorporated into the modelling process using a binary categorical indicator with persons that have no health limitation forming the reference category. The second health measure - of self rated health - also takes a binary form. Respondents with good, very good or excellent self reported general health are amalgamated into one group and those that report fair or poor health form a second. The first of these is the designated reference category. One hundred and nine women - which is 7% of the studied households - reported fair or poor health on their first ELSA interview, with 7.2% of male partners doing so. The incidence of both limiting health and poor self rated health is similar amongst older women and their spouses, and of particular interest is the impact of these health issues on both a person’s own employment and that of their spouse. This will be investigated further in the later modelling process as part of analysis addressing the first and third research questions. The third health variable indicates a decline in health status; 8.9% of women and 11.3% of their partners registered the onset of a limiting health condition during their observation window. This is not a baseline measure, but rather one that signifies a change in status over a period of time.

The caring obligations of ELSA participants are assessed using an item that asks whether they had looked after anyone in the past week; amongst the sampled women 297 (18.9%) responded positively. This is double the rate observed within the male partner sample, of 8.9%, and reflects the gender imbalance in caring obligations raised in the literature review of Chapter 1. Caring responsibilities are indicated in the modelling process with a binary indicator, with the reference group formed from those who had not recently provided care.

**Income and working patterns of women and male partners**

A respondent’s total income is derived from employment, self employment, private and state pensions, benefits and any other sources. The baseline weekly incomes for the women’s and male partner samples are graphed in Figure 2.4. Note that the incomes of two women and one male partner are excluded from these plots; they were particularly large values greater than £4000. The median income for each distribution is indicated with a dashed vertical line. The median income for the sampled women of £187 is lower than the male partner median of £346 - this is particularly noteworthy given the differences in the age distribution and
employment status of the two samples. Whilst all women in the sample are aged between 50 and 59 at baseline, their spouses include men as young as 31 and as old as 87; also, all women are employed at baseline, but 16% of the male partners were either retired, long term sick and disabled, unemployed or in a caring role. Despite this male partner incomes are, on average, higher than those of the women in the households. This is a likely consequence of a greater proportion of older women working part time and a tendency for women’s earnings from employment to be less than those of their male counterparts. In the modelling process total income is configured as a log transformed continuous measure.

The incidence of part time working is considerably higher amongst the older women in the studied households. Part time employment is defined as less than 35 hours per week, and 55.2% of women had this type of working pattern at baseline compared to 10.7% of the male partners. A binary indicator representing working hours is constructed using full time employees as the reference group.

**Partner’s employment status**

The impact of male partner’s employment status on women’s retirement pathways is of particular interest in this research. Male spouses are categorised as either employed, retired or in an alternative non-working state of illness, caring or unemployment. As figures in Table 2.3 on page 87 show, of the 1569 couples in the women’s sample 1318 or 84% had both

![Figure 2.4: Income distribution at baseline for women and male partners](image)
members employed. In 150 (9.6%) of households the female member was working and her partner was retired, whilst in the remaining 101 (6.4%) the male partner was in a state of either illness, unemployment or caring for home and family. Configuring the male partner’s employment status in this way facilitates a detailed investigation of the impact that the male spousal labour market position has on women’s employment trajectories, but it is not possible in this research to examine the effect of the women’s employment position on the male partner’s transitions. This is a consequence of the sample selection criteria - households are selected on the basis that they contain an employed woman, with no restriction placed on the labour market status of the male partners. Male spouses are categorised as either employed, retired or in an alternative non-working state, but all women are designated as employed. It is therefore possible to examine the impact of male partner’s status on women’s retirement pathways, but not the reverse; to do so would require sampling women in alternative labour market positions, but the research questions of this thesis relate to working women.

Social class and education

ELSA respondents in the studied households are categorized into one of three social class groups of managerial/professional, routine/manual and intermediate occupations. These categories, and the percentage of persons in each, are shown in Table 2.3 on page 87 for both women and their male partners. The two samples differ in that a greater proportion of the men are classified as managerial/professional; 46.7% of male partners are in this group compared to 37.0% of women. However, only 20.3% of male spouses have an intermediate social class compared to 28.7% of females. The gender difference is smaller in the routine/manual social class group with 34.2% of women categorised as such, compared to 33.0% of male partners. For each gender social class is operationalized as a categorical variable with the managerial/professional group the designated reference category.

Education is also structured as a categorical measure. There are three levels; the highest contains persons with higher than A level post-secondary education, whilst the middle group are those with no higher than a secondary level qualification. The lowest group, which forms the reference category, is comprised of persons with lower than an O level or equivalent mid-secondary qualification. Table 2.3 shows the percentage of women and male partners with
each education level as measured at the time of first entry into ELSA. The greatest difference between the genders is seen amongst the most educated group, with 31.0% of women having higher than A level or equivalent qualifications compared to 37.5% of the male partners. The gender difference is lowest amongst those with the least education with 32.4% of women and 29.8% of male partners in this group. The middle O level or equivalent category contains 36.6% of women and 32.7% of men.

2.6.3 Household measures

Household pension wealth, non pension wealth, tenure and the presence of children are the household factors examined in this research. Both the woman and male partner of the studied couples are allocated the same value or status of these measures. The influence of pension wealth on women’s employment trajectories is of primary interest and the structure of this variable requires detailed consideration; the definition and form of the household financial factors are therefore considered separately in the next section. Here, the structure of the tenure and presence of children variables are briefly explained.

Tenure

A couple’s housing status is given as one of three possibilities - outright ownership, renting or as having an outstanding mortgage. Families are allocated to one of these groups according to their status on their first ELSA interview and are assumed to remain with that same status throughout their observation period. Table 2.4 shows the proportion of couples in each of the women’s and men’s sample that have the specified type of tenure. As explained earlier missingness in male partner measurements has led to a difference in the number of couples included in each of these samples. Consequently, whilst both the female and male members of each couple are allocated the same tenure status there are fewer couples in the men’s sample, and this causes some minor differences in the observed incidence of each tenure type between the two. Approximately 35% of couples in this study own their homes outright, with 57.3% of the observed women in properties with an outstanding mortgage and 6.9% living in rented housing. This information is operationalized with a categorical tenure variable that has persons who own their homes outright as the reference group.
Table 2.4: Observed household level sample statistics for women’s and male partner samples at time of first ELSA response

<table>
<thead>
<tr>
<th>Variable</th>
<th>Levels</th>
<th>Women</th>
<th></th>
<th></th>
<th></th>
<th>Male partners</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>n</td>
<td>%</td>
<td>n</td>
<td>%</td>
<td>n</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>Tenure</td>
<td>Own outright</td>
<td>562</td>
<td>35.8</td>
<td>424</td>
<td>34.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Outstanding mortgage</td>
<td>899</td>
<td>57.3</td>
<td>744</td>
<td>60.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rent</td>
<td>108</td>
<td>6.9</td>
<td>62</td>
<td>5.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent child</td>
<td>No</td>
<td>1278</td>
<td>81.5</td>
<td>990</td>
<td>80.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>291</td>
<td>18.6</td>
<td>240</td>
<td>19.5</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Presence of children in the household**

A dependent child is defined as a person aged 17 or under who earns less than £5000 per year, and this can include grandchildren. Figures in Table 2.4 show that approximately 19% of the studied households have a resident dependent child. A binary variable is formulated from this information using couples with no dependent children as the reference category.

2.6.3.1 Measures of household wealth

The employment trajectories of women from households with varying levels of pension wealth are of primary interest in this research, with non pension wealth also incorporated. The definition and structure of each of these measures is considered here.

**Household pension wealth**

The pension wealth measure used in this thesis is the total accumulated private and state pension wealth for both members of the studied couples. In this section we consider the form that this measure could take for subsequent analysis. This is a pertinent issue because, whilst wealth is available as a continuous measure in ELSA, it has a highly skewed distribution in this sample; the lowest level of total pension wealth recorded for the coupled households is £25,390, the highest is £8,108,000 and the median value approximately £35,000. Structuring this variable into a categorical form would facilitate easier interpretation of the impact of wealth, but it may result in inaccurate estimates for women at the extreme end of the distribution. Consider, as an example, the households grouped into five quintiles based on the amount of wealth held when the female member was aged 55. Table 2.5 shows the
range of values within each quintile. The difference in wealth is particularly large within the lowest and highest groups. The poorest household in the lowest group has accumulated £25,400, but the richest household in this same group has £212,000. These two families are both placed into the same quintile group despite one having wealth that is over eight times that of the other, and the modelling process assumes an identical effect of the wealth on the women’s likelihood of staying in work. Similarly amongst the most affluent households that are placed into the highest quintile, the wealthiest couple has £7.5 million more in pension resources than that observed at the bottom end of this group, and yet in the modelling process it is assumed the impact of this wealth on transition rates is assumed the same. The effects estimated from the model apply to all women within a particular group, but any group may contain women with very different levels of pension wealth. In this section we consider what an appropriate coding of the pension wealth variable might be, with a particular focus on the highest end of the wealth distribution.

Table 2.5: Minimum and maximum pension wealth values for quintiles at age 55 (£000s)

<table>
<thead>
<tr>
<th>Quintile</th>
<th>Lowest</th>
<th>Second lowest</th>
<th>Middle</th>
<th>Second highest</th>
<th>Highest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum pension wealth</td>
<td>25.4</td>
<td>212</td>
<td>307</td>
<td>433</td>
<td>617</td>
</tr>
<tr>
<td>Maximum pension wealth</td>
<td>212</td>
<td>307</td>
<td>433</td>
<td>617</td>
<td>8108</td>
</tr>
<tr>
<td>Range</td>
<td>186</td>
<td>95</td>
<td>126</td>
<td>184</td>
<td>7491</td>
</tr>
</tbody>
</table>

The aim of the following analysis is to determine if there is a group of women from wealthy households that have a significantly different risk of leaving work than their less affluent counterparts. Note that figures here are calculated from a restructured form of the dataset that differs from that used elsewhere in this chapter. In this ‘long form’ structure women have multiple records with one for each year of age that they are either at risk of leaving work or have an observed transition. There are a total of 6182 records for the 1569 women in the study. This sample is divided into two groups according to whether the accumulated pension resources at each age is higher than or less than a given percentile. The percentiles of interest rise in 5% increments from the 70th to the 95th, with the 99th percentile also included to contrast the most extreme end of the wealth distribution. The number of women and records where wealth is greater than each percentile is shown in Table 2.6.
Of the 1569 women in the dataset 584 have pension wealth values greater than the 70th percentile - that is, they are in the top 30% of the wealth distribution - and these women contribute 1866 records. There are 1559 records from 499 women in the top 25% and so on as detailed in the table, ending with 66 observations from the 31 respondents who are in the wealthiest 1% of the sampled couples.

Table 2.6: Number of sampled women, records and transitions above a range of pension wealth percentiles

<table>
<thead>
<tr>
<th>Percentile of wealth distribution</th>
<th>70%</th>
<th>75%</th>
<th>80%</th>
<th>85%</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of women above percentile</td>
<td>584</td>
<td>499</td>
<td>421</td>
<td>324</td>
<td>228</td>
<td>128</td>
<td>31</td>
</tr>
<tr>
<td>Number of records above percentile</td>
<td>1866</td>
<td>1559</td>
<td>1250</td>
<td>942</td>
<td>636</td>
<td>325</td>
<td>66</td>
</tr>
<tr>
<td>Number of transitions above percentile</td>
<td>89</td>
<td>80</td>
<td>68</td>
<td>56</td>
<td>40</td>
<td>23</td>
<td>7</td>
</tr>
</tbody>
</table>

For each of the seven wealth groups a binary indicator is used to designate membership; it is coded 1 if a woman has sufficient accumulated household pension wealth to place her in the top given percentage of households. The indicator takes value 0 if she has insufficient wealth to be in that upper proportion. A series of discrete time event history models for the probability of transitioning are then fitted that incorporate, in turn, each of the seven binary indicators and appropriate individual level predictors. In the interests of space, detailed results of these models are not reproduced here, but are specified where appropriate in the following summary.

The above process leads to seven estimated coefficients - one for each of the percentiles in question - and these are shown graphically in Figure 2.5. In this figure each of the estimates is plotted with a 95% confidence interval. Starting at the bottom of the graph, the confidence interval for women in top 30% of the wealth distribution spans 0. This indicates that the probability of transitioning out of work for these women is not significantly different than it is for women in the lowest 70% of the sample. A similar conclusion is found for women in households that are in the top quarter of the wealth distribution; there is no statistically significant difference between their transition rate and that for women who fall in the lowest 75% for pension wealth.

The conclusion changes, however, for women in households that are in the highest 20% of the wealth distribution. There is evidence to suggest that the probability of these women
transitioning is higher than it is for women with fewer pension resources; with an estimated coefficient from the model of 0.3611, it corresponds to an increase in risk of 43.5%. If we consider a more tightly defined wealth group - of women in the upper 15% of the distribution - then they have an estimated coefficient of 0.4768 which corresponds to an increased risk of 61.1% compared to women in the lowest 85% of households. Being in the top 10% has a similar effect with an estimated increase in hazard of 63.7% (from a coefficient of 0.4930). Women in the wealthiest 5% of couples have a risk of leaving work that is 73.9% higher than it is for women in the lower 95% (estimated coefficient is 0.5531).

The level of variability in these estimates is similar, regardless of the level of wealth. For women in the wealthiest 15, 10 and 5% of households the confidence limits are not markedly different. Where both the estimate and uncertainty surrounding the estimate does change, however, is in the extreme end of the wealth distribution. The top line of Figure 2.5 plots values for women who are placed in the highest 1% of households for accumulated pension resources. These women are predicted a hazard rate that is 193% higher than women in the rest of the sample (from a coefficient of 1.076), but there is considerable uncertainty surrounding this estimate. The predicted risk differential could be as low as 35.6%, or as high as 534%.

These results indicate that there is a positive relationship between pension wealth holdings and transition rates; the higher the level of pension wealth, the greater the risk of a
woman leaving work. However there are not overly large differences between the confidence intervals of women that are in the highest 20%, 15%, 10% or 5% of couples for pension wealth resources. It is only those with very extreme levels of household wealth that have a considerably higher - and markedly more uncertain - estimated risk of leaving work.

From this, it seems reasonable to code the pension wealth variable by grouping together the 1250 observations taken from women in the top 20% of the pension wealth distribution - but ideally with the 66 records from the top 1% separated out, because their transition behaviour varies markedly from the others. An event history model fitted with all 1250 observations grouped together would predict the same pension wealth effect for all of the women when evidence here suggests there is variation between the top 1% and the remainder. However this is not a feasible option - the top 1% of observations involve only 7 transitions which is too few to place into a single category. Recoding the continuous measure into quintiles seems the most sensible choice; it would adequately allow the modelling of the transitions of the more affluent women in the sample and perhaps underpredict the risk of only a small proportion.

Given the above conclusion, pension wealth will be represented in the modelling process as a time-varying five category measure. Women are first divided into groups of the same age and each age group is then sorted into five quintiles according to the total amount of state and private pension wealth women and their partners have accrued. The wealthiest quintile is designated as the reference category. Both members of each household are allocated the same quintile group with male partners designated as belonging to the same quintile as their spouse.

**Non pension wealth**

The combined value of a couple’s non pension resources is calculated from housing and non-housing wealth. Non-housing wealth includes financial assets (excluding pension wealth), business value and other property assets. Figures are given net of debt. The amount of any outstanding mortgage is not included in this measure, but having a mortgage commitment is indicated separately in the tenure variable.

The total wealth measure is configured in a similar way to the pension wealth covariate,
Table 2.7: Assignment of households to non pension and pension wealth quintile groups at baseline

<table>
<thead>
<tr>
<th>Non pension wealth quintile</th>
<th>Pension wealth quintile</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Total</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lowest</td>
<td>n</td>
<td>%</td>
<td>n</td>
<td>%</td>
<td>n</td>
<td>%</td>
<td>n</td>
<td>%</td>
</tr>
<tr>
<td>Lowest</td>
<td>104</td>
<td>33.3</td>
<td></td>
<td>60</td>
<td>19.2</td>
<td>40</td>
<td>12.8</td>
<td>46</td>
<td>14.7</td>
</tr>
<tr>
<td>Fourth</td>
<td>10</td>
<td>3.1</td>
<td></td>
<td>143</td>
<td>45.0</td>
<td>78</td>
<td>24.5</td>
<td>62</td>
<td>19.5</td>
</tr>
<tr>
<td>Third</td>
<td>26</td>
<td>7.8</td>
<td></td>
<td>100</td>
<td>30.0</td>
<td>77</td>
<td>23.1</td>
<td>71</td>
<td>21.3</td>
</tr>
<tr>
<td>Second</td>
<td>53</td>
<td>17.4</td>
<td></td>
<td>64</td>
<td>21.1</td>
<td>52</td>
<td>17.1</td>
<td>63</td>
<td>20.7</td>
</tr>
<tr>
<td>Highest</td>
<td>85</td>
<td>28.2</td>
<td></td>
<td>36</td>
<td>12.0</td>
<td>48</td>
<td>15.9</td>
<td>58</td>
<td>19.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
in that women of the same age are ranked and divided into quintile groups. The relationship between the two wealth variables is shown in Table 2.7 on page 97. Figures in this table show the assignment of women to pension wealth groups for each of the non pension wealth quintiles. As an example, of the 312 women in the lowest non pension wealth group 104, or 33.3%, were also in the poorest pension wealth quintile. Sixty women (19.2%) were in the second pension wealth quintile whereas nearly one fifth (19.9%) were in the wealthiest pension group. The figures in this table show that a significant proportion of women are not placed in the same quintile group for both wealth measures. Two thirds of those in the poorest non pension wealth quintile were allocated a different pension wealth group, whilst 55% of women from the fourth were. From each of the third, second and wealthiest non pension wealth groups respectively, 76.9%, 79.3% and 75.4% of women were placed into a different quintile for pension assets. This relatively low level of correspondence across the two measures justifies the inclusion of both in the analysis.

2.7 Summary

This chapter has detailed the data and modelling approach that will be used to address the research questions of this thesis. The English Longitudinal Study of Ageing is a unique dataset in that it provides repeated measurements of older person’s individual attributes as well as household characteristics, including detailed information on respondents’ health, employment and financial circumstances. We sample 1569 households to examine women’s retirement patterns, and 1230 couples for the analysis of male partner transitions. To address the first and third research questions - which relate to the influence on employment exit of partner health, partner employment status and household pension wealth - a series of discrete time event history models will be fitted to each of the older women and male partner samples. A yearly age scale is the chosen metric for time in each case, and models are estimated under a conditional likelihood framework in which it is assumed that the first transition observed is the first that occurs. A detailed exposition of the models for women’s transitions is given in Chapter 3 whereas male partner models are presented in Chapter 5.

The second research question of this study investigates the differential impact of partner health, employment status and accumulated household pension wealth on women’s retire-
ment trajectories. In this chapter we specified the logistic regression model that will be fitted to the sample of transitioned women to determine whether there is any difference in the predictors of voluntary versus involuntary exit pathways. Results from this process are detailed in Chapter 4.

In both the event history and logistic regression models covariates are organised according to measurement level. Individual characteristics include sociodemographic control measures for education, social class and income whereas predictors of primary interest are those for caring responsibilities, health and working hours. Household level attributes are tenure, the presence of dependent children and pension and non pension wealth. Partner measures include control variables for income and age as well as the key indicators for health and employment status. In this chapter the ELSA questions relating to these measures were described, and their incidence in the sampled data was detailed. A particular strength of event history models is the capacity to incorporate time varying indicators as any change in health or financial status is accounted for in the modelling process.
Chapter 3

Coupled women’s transitions from employment

3.1 Introduction

Possible predictors of older women’s labour market exit in the United Kingdom are examined in an emerging body of literature (Loretto and Vickerstaff, 2013; Duberley et al., 2014) with individual, partner and family attributes identified as relevant to the retirement decision. However these studies use primarily qualitative methods with limited generalizability. In this thesis discrete time event history models are fitted to large scale survey data from the English Longitudinal Study of Ageing - an approach that allows us to establish the statistically significant predictors of women’s labour market exit and quantify their impact.

The first research question was formally stated in Chapter 1 and asks whether the household context modifies the effect that women’s own individual attributes have on their chances of staying in the labour market. In this chapter we focus on the specific household configuration of coupled women who reside with their spouse or partner, and consider the influence of the male partner’s health and employment status, and joint pension wealth on the timing of the female member’s transition out of work. In the next section the modelling approach - that was formally detailed in Chapter 2 - is briefly summarised. The relationship between age and the transition probability is developed in Section 3.3, relevant individual level predictors are established in Section 3.4 and household attributes introduced in Section 3.5. Partner circumstances are the subject of Section 3.6. Model fit and diagnostic measures are evaluated
in Section 3.7 and the role of unobserved factors is considered in Section 3.8. Interpretation of results is given in Section 3.9 and the chapter ends with a summary in Section 3.10.

3.2 Method

The event history model for estimating women’s transitions was fully explained in Chapter 3 and is detailed again here for convenience. A fixed effects model is fitted first, as expressed in Equation 3.1.

\[
\log(-\log(1 - p_{it})) = \alpha^T z_{it} + \beta^T x_{it} \tag{3.1}
\]

The cloglog link transformed outcome, \( p_{it} \), is the conditional probability that a transition occurs at age \( t \) for individual \( i \). The baseline hazard function, \( \alpha^T z_{it} \), expresses the relationship between age and the probability of exit and covariates and corresponding parameter estimates are contained in \( \beta^T x_{it} \). This model is fitted to the ELSA sample of 1569 women in a series of stages. The first is the estimation of the baseline hazard function, in a process that tests linear and higher order polynomials to determine which best captures the relationship between the probability of a transition occurring and a woman’s age. This is explained in Section 3.3. Following that, covariates are introduced with individual, household and partner level measures incorporated in turn. The model is further developed in Section 3.8 with the addition of a random intercept term to account for unobserved time invariant characteristics, as denoted by \( u_i \) in Equation 3.2.

\[
\log(-\log(1 - p_{it})) = \alpha^T z_{it} + \beta^T x_{it} + u_i \tag{3.2}
\]

3.3 The baseline hazard function

The first stage in fitting the discrete time event history model specified in Equation 3.1 is to determine the baseline hazard function. This describes how the conditional probability of employment exit varies as women approach state pension age. It is estimated from the sample transition rate for each year of women’s age between 51 and 59; these sample rates were first given in Table 2.2 of Chapter 2 and are reproduced for convenience in Table 3.1.
below. At age 51 3.3% of women had an observed transition, whilst the lowest rate of 2.1% was recorded for 53 year olds. The highest number of transitions occurred at age 59, with an observed exit rate of 9.0%. These figures show an overall increasing likelihood of exit as women approach state pension age, but lower observed rates at ages 52 and 53 suggest a possible non-linear trend.

Table 3.1: Sample transition rate for each year of women’s age

<table>
<thead>
<tr>
<th>Sample statistics</th>
<th>51</th>
<th>52</th>
<th>53</th>
<th>54</th>
<th>55</th>
<th>56</th>
<th>57</th>
<th>58</th>
<th>59</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of women of this age</td>
<td>543</td>
<td>643</td>
<td>758</td>
<td>760</td>
<td>806</td>
<td>774</td>
<td>754</td>
<td>668</td>
<td>476</td>
</tr>
<tr>
<td>Number of women’s transitions</td>
<td>18</td>
<td>16</td>
<td>16</td>
<td>30</td>
<td>32</td>
<td>36</td>
<td>44</td>
<td>52</td>
<td>43</td>
</tr>
<tr>
<td>Women’s transition rate (%)</td>
<td>3.3</td>
<td>2.5</td>
<td>2.1</td>
<td>3.9</td>
<td>4.0</td>
<td>4.7</td>
<td>5.8</td>
<td>7.8</td>
<td>9.0</td>
</tr>
</tbody>
</table>

The first fitted form of the baseline hazard function is a general specification which includes a binary indicator for each year of age between 51 and 59. Parameter estimates and confidence intervals for this model are given in Table 3.2. This specification is optimal in terms of fit and has the lowest deviance, calculated as the negative of twice the log likelihood value (Singer and Willett, 2003). However in this instance the general specification requires nine predictors and in the interests of parsimony other polynomial versions are considered. A linear version is estimated and results are given in Model 2, Table 3.2. As expected the deviance is higher than that of the general specification, with values of 2265.596 and 2272.488 respectively; this indicates the linear model does not predict as well as the general specification. It does, however, have the advantage of requiring only a constant and linear term. The third estimated version for the baseline hazard is a quadratic model that includes a squared age indicator. Parameter estimates and confidence intervals for this are given as Model 3 in Table 3.2. However the inclusion of the additional squared term does not significantly improve model fit when compared to the linear version ($\chi^2(1) = 0.1259, p = 0.1259$); the linear specification is therefore adopted.

The linear baseline hazard function estimates the relationship between age and the conditional probability of women’s transition from employment as $-4.019 + 0.178 \times \text{Age}$. As expected this shows an increasing predicted risk as women grow older, with the additional risk for each year past 50 estimated at $(e^{0.178} - 1) \times 100 = 19.5\%$. These estimates are
based only on age with no consideration of women’s other individual or household level attributes. In subsequent sections of this chapter covariates representing individual, household and partner attributes are added to this baseline model and assessed for significance.

Table 3.2: Parameter estimates for the baseline hazard function from discrete time event history models for the conditional probability of women’s transition from employment

<table>
<thead>
<tr>
<th></th>
<th>General specification</th>
<th>Linear baseline</th>
<th>Quadratic baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Binary age indicators</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 51</td>
<td>-3.390***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.852,-2.928)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 52</td>
<td>-3.681***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.171,-3.191)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 53</td>
<td>-3.847***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.337,-3.358)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 54</td>
<td>-3.212***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.570,-2.854)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 55</td>
<td>-3.206***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.553,-2.860)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 56</td>
<td>-3.044***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.371,-2.718)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 57</td>
<td>-2.811***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.107,-2.516)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 58</td>
<td>-2.513***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.785,-2.241)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 59</td>
<td>-2.357***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.656,-2.058)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Continuous age variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.178***</td>
<td>-0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.128,0.229)</td>
<td>(-0.236,0.231)</td>
<td></td>
</tr>
<tr>
<td>Age^2</td>
<td></td>
<td>0.017</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.004,0.038)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-4.019***</td>
<td>-3.626***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.341,-3.697)</td>
<td>(-4.202,-3.051)</td>
<td></td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>6,182</td>
<td>6,182</td>
<td>6,182</td>
</tr>
<tr>
<td><strong>Log Likelihood</strong></td>
<td>-1,132.798</td>
<td>-1,136.244</td>
<td>-1,135.073</td>
</tr>
<tr>
<td><strong>Akaike Inf. Crit.</strong></td>
<td>2,283.597</td>
<td>2,276.487</td>
<td>2,276.145</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

3.4 Individual level predictors

The first research question refers to the influence of partner and household characteristics on older women’s employment exit; we are interested in which of these are significant predictors and how they modify the effects of women’s individual level attributes. The significance and magnitude of these individual level effects are established first, in this section. Possible predictors are categorized into non voluntary factors including health and caring responsi-
bilities, and working patterns and attitudinal effects. Individual level predictors within each these categories are discussed in Section 3.4.2. Prior to this, the control factors of education, social class, income and having a dependent child are incorporated into the baseline model; their inclusion facilitates more accurate estimation of the health, caring and employment effects that are of primary interest.

### 3.4.1 Control factors

The preferred linear baseline model describes the relationship between the conditional probability of a woman leaving work and her age. This is reproduced for convenience as Model 1 in Table 3.3 on page 106. For every year of age past 50 the risk of leaving work increases by 19.5%, which results from a coefficient of 0.178 on the cloglog scale. Control measures of education, social class, income, and an indicator for dependent children are incorporated into this baseline model and results are given in Table 3.3, Model 2. These factors are retained irrespective of their statistical significance, because whilst they are not of primary interest as predictors of labour market exit, their inclusion does result in changes to the estimated hazard rates. These adjustments are briefly summarized here.

The exponentiated coefficients of the categorical variables in this model specify the additional estimated risk of transition for a woman with the given attribute compared to a woman from the reference category for that measure. Those with the highest level of education - that is, post-secondary qualifications that are higher than A-level equivalent - have an estimated $(e^{0.081} - 1) \times 100 = 8.4\%$ increase in their conditional probability of leaving work compared to women educated to less than O level. In contrast, women educated to between O and A level have a decreased risk of exit compared to those with the least education, by an estimated $(1 - e^{-0.258}) \times 100 = 22.7\%$.

Estimated coefficients for social class suggest that women from both intermediate and routine/manual classes have a higher probability of transitioning out of employment than women in professional and managerial classes - the risk differential for routine/manual women is 17.9\% and the effect is greater - at 29.3\% - for the intermediate group. Having a dependent child adjusts hazard downwards. Women with this additional responsibility are more likely to stay in work, with an estimated risk of leaving that is 12.6\% lower than
for women with no dependent children.

The baseline model is also adjusted for income, which is entered as a log transformed continuous measure. The estimated coefficient shows a negative relationship between earnings and conditional probability of exit. Higher income earners are predicted lower hazard rates which translates into an increased likelihood of staying in work. Women with lower personal incomes have higher estimated hazard rates and correspondingly lower chances of remaining in employment.

Retaining the education, social class, income and dependent children covariates in the baseline model allows the effects of health and caring responsibilities, employment and attitudinal factors to be separated out from the effects of these control variables. This gives a more accurate representation of the impact that the main predictors of interest have on women’s later life employment, and developing this is the focus of the next section.

3.4.2 Key interest predictors: proportional effects

In this section women’s non voluntary factors - of health and caring responsibilities - along with working patterns are discussed in turn. At this stage only proportional effects are examined with the assumption that the impact of any particular covariate is constant irrespective of age. This assumption is relaxed in the next stage of the analysis (presented in Section 3.4.3).

3.4.2.1 Non voluntary factors

Evidence from existing literature surrounding women’s later life employment indicates that poor health, deterioration in health and caring responsibilities are relevant to their chances of staying in work. Poor health and the onset of a limiting health condition are expected to be associated with early labour market exit, but the relationship between having caring duties and continued employment is less clear. Carers might be more likely to remain in work if their income is essential for economic wellbeing of the family; alternatively caring duties could be associated with a higher transition risk if the woman is the main provider of care.

Two measures of a woman’s current health status are considered in this analysis and a third indicates a decline in status. The presence of a long term condition that limits her activities is indicated by a binary variable, as is self rated health. The reference category for
Table 3.3: Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with proportional individual level covariates

<table>
<thead>
<tr>
<th></th>
<th>Linear baseline</th>
<th>Control variables</th>
<th>Health, caring</th>
<th>Part time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Age</td>
<td>0.178***</td>
<td>0.174***</td>
<td>0.170***</td>
<td>0.163***</td>
</tr>
<tr>
<td></td>
<td>(0.128, 0.229)</td>
<td>(0.124, 0.225)</td>
<td>(0.119, 0.221)</td>
<td>(0.112, 0.215)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td></td>
<td>-0.258*</td>
<td>-0.245</td>
<td>-0.234</td>
</tr>
<tr>
<td></td>
<td>(-0.555, 0.039)</td>
<td>(-0.542, 0.052)</td>
<td>(-0.530, 0.062)</td>
<td></td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td></td>
<td>0.081</td>
<td>0.055</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>(-0.262, 0.425)</td>
<td>(-0.291, 0.402)</td>
<td>(-0.298, 0.394)</td>
<td></td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.257</td>
<td>0.197</td>
<td>0.101</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.069, 0.583)</td>
<td>(-0.130, 0.525)</td>
<td>(-0.230, 0.433)</td>
<td></td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>0.165</td>
<td>0.061</td>
<td>-0.089</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.176, 0.507)</td>
<td>(-0.285, 0.408)</td>
<td>(-0.445, 0.267)</td>
<td></td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.135</td>
<td>-0.119</td>
<td>-0.140</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.448, 0.178)</td>
<td>(-0.432, 0.194)</td>
<td>(-0.453, 0.174)</td>
<td></td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.067**</td>
<td>-0.062*</td>
<td>-0.046</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.133, -0.002)</td>
<td>(-0.127, 0.004)</td>
<td>(-0.116, 0.023)</td>
<td></td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.470***</td>
<td>0.448***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.203, 0.736)</td>
<td>(0.181, 0.715)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.227</td>
<td>0.220</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.102, 0.557)</td>
<td>(-0.110, 0.550)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.435**</td>
<td>0.460**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.067, 0.802)</td>
<td>(0.092, 0.828)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decline in health (ref: constant health status)</td>
<td>0.337</td>
<td>0.334</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.260, 0.934)</td>
<td>(-0.264, 0.932)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-4.019***</td>
<td>-3.707***</td>
<td>-3.853***</td>
<td>-4.080***</td>
</tr>
<tr>
<td>Constant</td>
<td>6.182</td>
<td>6.182</td>
<td>6.182</td>
<td>6.182</td>
</tr>
<tr>
<td>Observations</td>
<td>-1,136.244</td>
<td>-1,130.582</td>
<td>-1,117.917</td>
<td>-1,112.339</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>2,276.487</td>
<td>2,277.165</td>
<td>2,259.834</td>
<td>2,250.677</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>2,276.487</td>
<td>2,277.165</td>
<td>2,259.834</td>
<td>2,250.677</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
this is good or better self rated health, with the alternative being an amalgamation of poor and very poor. Deterioration in health is also indicted with a binary measure that has a reference category of stable health. The caring indicator also has two categories and denotes whether a respondent recently provided caring assistance; there is no distinction made with respect to who care was provided for. Each of these health and caring covariates is entered as time varying and added to the most recent model that controls for education, social class, income and dependent children as detailed in the previous section. Results are given in Table 3.3, Model 3. Incorporating each of these health and caring factors does improve the fit of the model ($\chi^2(4) = 25.33, p < 0.001$). Note that this is one instance where the log likelihood ratio test for significance gives conflicting results from that of the Wald test; this possibility was first raised in Section 2.3.1. The limiting health and decline in health variables are not indicated in Table 3.3 as significant in the same manner as the self rated health and care variables. They are, however, significant when assessed through the likelihood ratio test which is the preferred method throughout this thesis.

The effect of the health and caring attributes is now discussed in more detail; results from the fitted model are presented and discussed below through the use of graphs. For each variable of interest there are two figures. Predicted values are plotted as lines on the probability scale to facilitate interpretation of parameter estimates and also on the transformed cloglog scale to help assess model fit and the need for non proportional effects. Observed transition rates from the sample are also graphed as points for this purpose. Observed and predicted probabilities are plotted for each value of the given covariate, whilst the levels of all other variables are held constant at either modal or median value.

**Limiting health**

Women in the studied ELSA sample are grouped with others of the same age, and then within each age group are subset again according to health status. The proportion of women with a limiting health condition, and who transitioned out of employment, is plotted for each year of age with a cross (+) in Figure 3.1a. The observed transition rate for healthy women is denoted by a solid circle (●). The same information is plotted on the transformed cloglog scale in Figure 3.1b.
Figure 3.1: Observed and predicted transition rates for women’s employment exit according to limiting health status
At the majority of ages a greater proportion of women from the limiting health group than from the healthy group transitioned out of work; the exceptions to this occur at age 51 where no transitions were observed amongst women with limiting conditions (hence no value is plotted), and at ages 52 and 56 where transition rates are marginally higher for healthy women. Additionally, the difference between the transition rates of the two groups is not constant across ages - it is greater for older women aged 57 to 59 than for those younger. Between the ages of 52 and 56 the maximum difference is 2.7 percentage points, but in the last three years this has increased to 7.6 points. These observations suggest having a limiting health condition may be associated with an increased risk of leaving work, and that the magnitude of this risk changes with age.

The results in Table 3.3, Model 3 show an estimated coefficient for limiting health of 0.227. As a positive value it confirms that women with limiting health conditions are at greater risk of leaving work than their healthier counterparts, and the exponentiated value of this coefficient quantifies the size of this risk differential. Because \( e^{0.227} = 1.255 \) the conditional probability of leaving work is predicted to be 25.5% higher for a woman with a health limitation than for a woman without. This is shown visually in Figure 3.1; superimposed on the observed values on each graph are two trajectories constructed using predicted values from the fitted model with coefficients given in Table 3.3, Model 3. These trajectories give the estimated transition probabilities at each year of age for a woman with consistent values of limiting health - the lower line for a subject with no limiting health condition at any point between the ages of 51 and 59, and the upper dashed line for women who do have a condition in each and every one of these years. This representation is a consequence of limiting health being a time varying measure; the value of this variable changes to reflect women’s health status at each of their given ELSA interviews. Consequently the composition of the two health groups varies at each age. A 51 year old woman who does not have limiting health will be grouped with other healthy 51 year old women, but should she subsequently develop a limiting condition, she will switch groups and be allocated to the limiting health set at the appropriate age. Changes are also possible in the other direction with movement from the limiting to the non limiting health category. The lines shown in Figure 3.1 are estimated trajectories for women who do not switch groups at any point; an individual is either desig-
nated healthy at age 51 as well as age 52, 53 and so on until at least age 59, or has health limitations at each age.

The vertical separation of the trajectories plotted in Figure 3.1 is quantified by the model coefficient - a constant 0.227 on the cloglog scale and 25.5% as a probability. This constant effect is invoked by one of two assumptions that apply to this model. The ‘proportional hazards’ assumption restricts the estimated effect of having a limiting condition to be constant across the age range; the impact of having a condition on the likelihood of leaving work is not increasing or decreasing as a woman ages. However this contradicts the point made earlier, that in the observed sample the difference in the transition rate for women with a health condition compared to those without appears greater for older women than it is for younger. Consequently the validity of this proportional hazards constraint is examined further in Section 3.4.3. The second assumption that applies here is that of linear additivity. Under this specification, the effect of limiting health does not depend on values of other covariates in the model - it is taken to be 24.6% irrespective of a woman’s additional attributes.

**Onset of limiting health condition**

The onset of a health condition is defined as the presence of a long term limiting illness after previously not having had such a condition. The crosses in Figure 3.2 on page 111 plot the observed proportion of women in each age group that are coded as experiencing such a deterioration in health. These women leave work at a consistently higher rate than those with a constant health status and this suggests a positive coefficient should result in the fitted model. The results from incorporating this indicator in the model are in Table 3.3, Model 3 and, as expected, the effect of the onset of a limiting health condition is estimated as positive at 0.337. In percentage terms this is an increase in risk of 40.1%. The lower solid trajectory plotted in Figure 3.2 is the estimated path for a woman who has no limiting condition at age 50 and suffers no subsequent limitation. The upper dashed line plots the trajectory for a woman with an early deterioration in health - with the onset of a limiting condition at age 51 her predicted risk of leaving remains consistently 40.1% higher than it is for her healthier counterpart.

The assumption that the effect of a deterioration in health is consistent at every year of
Figure 3.2: Observed and predicted transition rates for women’s employment exit according to onset of limiting health
age conflicts with the level of variability seen in Figure 3.2. However this variability is, to an extent, a manifestation of the way in which each subject’s value for limiting health has been determined for a given age. The women in this sample are interviewed at irregular ages - the age of entry varies and most are not observed at consecutive ages, but on occasions at least two years apart. Considering the employment trajectories of these women along a common age axis, therefore, results in missing covariate values for the vast majority of subjects. The missingness was addressed prior to analysis with values of limiting health in unobserved years assumed the same as those observed within pairings of consecutive ages. Values at ages 50 and 51 were assumed the same, at 52 and 53 the same and so on.

The consequence of this modified ‘last value carried forward’ strategy is seen in the crosses of Figure 3.2a. The onset of a limiting health condition is identified when a woman’s health status changes between two consecutive ages, from having no limiting condition to having a limiting condition. But, because of the method used for imputing missing values, this change is more likely to be detected at ages 54, 56 and 58 and this is contributing to the variability in the plotted onset values. There is no impact on the incidence of deterioration in health, because only the age of detection and not frequency of detection is affected. Consequently the estimated coefficient for the onset measure remains unaffected, with the impact of this strategy for dealing with missing values relevant to any interaction term between the onset measure and age rather than the main effect.

**Self rated health**

A third time-varying health measure, of self rated health, categorises women into two groups according to whether they have described their health as either ‘fair’ or ‘poor’, or as ‘excellent’, ‘very good’ or ‘good’. For simplicity the first of these groups is referred to as the ‘poor’ health group and the latter as having ‘good’ health. The observed proportion of women who left work from each category - for each year of age - is plotted in Figure 3.3a on page 113. The same information, but using the transformed cloglog proportion, is in Figure 3.3b. In both graphs a cross (+) denotes values for women with poor self rated health and solid circles (●) represent women in the ‘good’ category.

The observed proportion of women with poor health who leave work is, at the majority
Figure 3.3: Observed and predicted transition rates for women’s employment exit according to self rated health status
of ages, higher than the proportion of women in good health who do so. The results of Model 3, Table 3.3 confirm that there is a significant difference in risk between the two groups, and the magnitude of this difference is estimated as 0.435 on the cloglog scale. This translates to women with self rated poor health having a predicted conditional probability of leaving work that is 54.5% higher than their healthier counterparts. Figure 3.3 shows this risk differential visually with the plotting of two curves on each subfigure; because self rated health is entered as a time varying covariate the solid line represents the trajectory for women with consistently good self rated health between the ages of 51 and 59, and the dashed line for women in continually poor health. As was the case for the limiting health measure, the proportional hazards assumption also applies here. The effect of poor self rated health is estimated at 54.5% irrespective of a woman’s age; however in Figure 3.3b the difference between the observed transition rate for women with good health and that for women in poor health appears to oscillate. Consequently the validity of the proportional hazards assumption will be investigated further, in Section 3.4.3.

**Caring responsibilities**

Here transition rates for women who have caring responsibilities are compared to those for women without caring obligations. The observed transition rates are plotted on the probability scale in Figure 3.4a and the transformed cloglog scale in Figure 3.4b. In each of these graphs a cross (+) represents carers and circles (●) non carers. The proportion of women who have caring duties and left work is consistently higher than it is for women without care obligations; the only exception to this is for 54 year old women. The magnitude of the difference is estimated at 0.470 points on the cloglog scale, which when exponentiated converts to an increase in risk of 60.0%. In context, this indicates that women with caring responsibilities have an estimated probability of leaving work that is 60.0% percent higher than for women who have not recently had caring duties. How this effect might vary as women age is the subject of Section 3.4.3 below.
Figure 3.4: Observed and predicted transition rates for women’s employment exit according to caring responsibilities
Figure 3.5: Predicted proportional effects and observed women’s employment transition rates for part time and full time workers
3.4.2.2 Working patterns

Varying work patterns are considered in this analysis with the distinction between women employed full time and those who work part time. Part time employees are defined as women working less than 35 hours per week and 16% percent of the respondents in this sample were doing so on at least one of their interview dates. Part time employees are considered to have a lower level of attachment to the labour market than their full time counterparts and are expected to have a higher probability of leaving work. Evidence to support this is seen in Figure 3.5a where the observed transition rates are plotted for each of full time (symbolised with \( \bullet \)) and part time workers (denoted as +). There is an upward trend in the transition rates for both part time and full time employees, but at every age except for 58 a higher proportion of part time than full time workers left employment.

The results from incorporating the working hours covariate into the model are in Table 3.3, Model 4. As expected the effect is significant and positive; the estimated coefficient of 0.439 converts to a risk differential of 55.1%. This supports the hypothesis that part time workers have a lower attachment to the labour market than full time employees. However, it is assumed in the current model that this effect is constant irrespective of age whereas the plotted observed data in Figure 3.5a indicates otherwise. The vertical distance between the observed transition rates does vary across the age range and this suggests that as women get older, different working patterns have different effects on the hazard. Accounting for this requires the fitting of an interaction term with age and this is considered below in Section 3.4.3.

3.4.3 Key interest predictors: non proportional effects

The analysis and results presented in Section 3.4.2 quantify the impact that limiting health conditions, poor self rated health, deterioration in health, caring responsibilities and part time work have on the probability of labour market exit for older women. However the fitted models invoked an assumption of proportional hazards - that is, the effect of each of these variables was assumed constant over time. In this section the model is extended to incorporate non proportional effects which allow the impact of these covariates to differ with age; however an adjustment will not be made for the onset of a limiting health condition. As was explained earlier, the variability in this effect over time is at least partly an artificial
3.4.3.1 Health and caring factors

The final version of the event history model for women’s transitions with individual main effects is as specified as Model 4 in Table 3.3. This quantifies the impact of a limiting health problem on the conditional probability of leaving work as 24.6%; the influence of poor self rated health is estimated at 58.4% and the risk associated with caring responsibilities is approximately 56.5%. These effect sizes are estimated under the assumptions of proportional hazards - they are assumed to be constant irrespective of women’s age. Here we consider evidence that the influence of having a health issue or caring duties may vary with age. Testing for such non-proportional effects involves incorporating an interaction term between each of the given indicators and age. In each case the hypothesised relationship is a linear one, in that the relevant risk differential increases or decreases in constant increments.

The results for the non-proportional limiting health effect are given in Model 1, Table 3.4 on page 119. The interaction between age and limiting health is not statistically significant ($\chi^2(1) = 2.946, p = 0.0861$), suggesting that including this term does not improve model fit. The non-proportional effect for the self rated health measure is also not significant (results not shown, $\chi^2(1) = 0, p = 1$), and neither is the age interaction term for caring (Model 2, Table 3.4, $\chi^2(1) = 0, p = 1$). Given these results each of the limiting health, self rated health and caring indicators are retained in the model as main effects only. Note, however, that these results show only that there is no linear effect between age and each factor; there might still be a non-proportional relationship that takes a different functional form. However accounting for this would require more complex terms to be fitted and in the interests of parsimony this issue is not explored further.

3.4.3.2 Part time working patterns

The part time working covariate is currently indicated as a main effect in the model with the assumption that the effect on the transition probability does not change as women age. It is estimated at a constant 55.1% increase. An interaction term between part time working and age is incorporated to account for a possible non-proportional effect; this configuration
Table 3.4: Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with non proportional individual level covariates

<table>
<thead>
<tr>
<th></th>
<th>Age:limiting health (1)</th>
<th>Age:caring (2)</th>
<th>Age:part time (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.141***</td>
<td>0.157***</td>
<td>0.297***</td>
</tr>
<tr>
<td></td>
<td>(0.084,0.198)</td>
<td>(0.098,0.216)</td>
<td>(0.202,0.392)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.231</td>
<td>-0.233</td>
<td>-0.239</td>
</tr>
<tr>
<td></td>
<td>(-0.527,0.066)</td>
<td>(-0.529,0.063)</td>
<td>(-0.535,0.057)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>0.052</td>
<td>0.048</td>
<td>0.059</td>
</tr>
<tr>
<td></td>
<td>(-0.293,0.398)</td>
<td>(-0.298,0.394)</td>
<td>(-0.286,0.404)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.102</td>
<td>0.101</td>
<td>0.101</td>
</tr>
<tr>
<td></td>
<td>(-0.230,0.434)</td>
<td>(-0.231,0.433)</td>
<td>(-0.231,0.433)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.086</td>
<td>-0.091</td>
<td>-0.098</td>
</tr>
<tr>
<td></td>
<td>(-0.442,0.269)</td>
<td>(-0.447,0.265)</td>
<td>(-0.454,0.258)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.134</td>
<td>-0.139</td>
<td>-0.153</td>
</tr>
<tr>
<td></td>
<td>(-0.448,0.179)</td>
<td>(-0.452,0.175)</td>
<td>(-0.467,0.161)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.047</td>
<td>-0.047</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(-0.117,0.023)</td>
<td>(-0.116,0.023)</td>
<td>(-0.113,0.025)</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.449***</td>
<td>0.288</td>
<td>0.440***</td>
</tr>
<tr>
<td></td>
<td>(0.182,0.716)</td>
<td>(-0.472,1.047)</td>
<td>(0.173,0.707)</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>-0.446</td>
<td>0.222</td>
<td>0.216</td>
</tr>
<tr>
<td></td>
<td>(-1.305,0.414)</td>
<td>(-0.108,0.551)</td>
<td>(-0.115,0.547)</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.449**</td>
<td>0.457**</td>
<td>0.472**</td>
</tr>
<tr>
<td></td>
<td>(0.080,0.818)</td>
<td>(0.089,0.825)</td>
<td>(0.103,0.841)</td>
</tr>
<tr>
<td>Decline in health (ref: constant health status)</td>
<td>0.233</td>
<td>0.332</td>
<td>0.368</td>
</tr>
<tr>
<td></td>
<td>(-0.376,0.842)</td>
<td>(-0.266,0.930)</td>
<td>(-0.230,0.967)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>0.437***</td>
<td>0.441***</td>
<td>1.606***</td>
</tr>
<tr>
<td></td>
<td>(0.174,0.699)</td>
<td>(0.178,0.703)</td>
<td>(0.859,2.354)</td>
</tr>
<tr>
<td>Age:limiting health</td>
<td>0.112*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.018,0.241)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age:recently provided care</td>
<td>0.027</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.091,0.145)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age:part time</td>
<td></td>
<td>-0.194***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.307,-0.081)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-3.947***</td>
<td>-4.039***</td>
<td>-4.897***</td>
</tr>
<tr>
<td></td>
<td>(-4.573,-3.322)</td>
<td>(-4.675,-3.404)</td>
<td>(-5.709,-4.086)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,182</td>
<td>6,182</td>
<td>6,182</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-1,110.866</td>
<td>-1,112.239</td>
<td>-1,106.455</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>2,249.733</td>
<td>2,252.479</td>
<td>2,240.910</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
permits the impact of age to change linearly over time. Results in Model 3 of Table 3.4 show this term is statistically significant ($\chi^2(1) = 11.768, p < 0.01$), and it is retained in the model.

The resulting trajectories for women who work part time for the duration of the studied age range, and for women who remain in full time work throughout, are graphed in Figure 3.6a (page 121) as probabilities and in Figure 3.6b on the cloglog scale. A woman working part time is more likely to leave her employment than if she were working full time hours and this holds until near retirement age; after 58 a part time employee is more likely to stay working than if full time. Whilst the hazard for both employment types increases with age, for each additional year the predicted probability of leaving work increases more for a woman working full time than it does for a part time worker. At age 51 a woman working part time is estimated three times more likely to leave work than a 51 year old full time employee; by age 55 this has decreased to twice as likely and, by age 59, she is predicted a lower probability of leaving. The model coefficients in Table 3.4, Model 3, quantify this non proportional effect as -0.194 on the cloglog scale. Transformed, this corresponds to a decrease in the effect of part time working of 17.6% for every year that a woman ages.

### 3.4.4 The effects of individual level attributes - summary

The variables for caring responsibilities, self rated and limiting health and onset of limiting health - along with main and age interaction terms for part time working - are combined into one model to give the final individual level specification. This model additionally controls for women’s education, social class, income and dependent children. Coefficients and their confidence intervals are as given in Table 3.4, Model 3. To briefly summarise, according to this model women with caring responsibilities are estimated 55.3% higher risk of leaving work than women without caring duties, and women with poor or fair self rated health are predicted a 60.3% greater risk than women with good or better self rated health. Having a limiting health condition increases the hazard by 24.1% whereas the onset of such a condition raises the risk by 44.5%. These increases in hazard are constant irrespective of a woman’s age. The impact of working hours does vary over time, and figures in Table 3.5 detail the predicted probability of leaving work for both part time and full time employees. At ages 51 to 58 women working part time are estimated a higher risk of leaving work than those
Figure 3.6: Observed and predicted women’s employment transition rates for part time and full time workers with age interaction
full time - although with a range of 0.3 to 2.5 percentage points the differences are not large. A second difference between the effect of working full time and part time is the rate with which the hazard rate changes over time; the risk of a full time employee leaving increases at a greater rate as state pension age approaches. Part time workers have a lower increase in risk over time.

Table 3.5: Predicted conditional probability of women’s transition by working hours (%)

<table>
<thead>
<tr>
<th>Working hours</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>51</td>
</tr>
<tr>
<td>Full time (35+ hours per week)</td>
<td>0.8</td>
</tr>
<tr>
<td>Part time (&lt;35 hours per week)</td>
<td>3.2</td>
</tr>
<tr>
<td>Percentage point difference</td>
<td>2.4</td>
</tr>
</tbody>
</table>

The first research question of this thesis asks whether labour market exit of older women is influenced by the household context, with family financial resources and partner characteristics modifying the effects of individual level attributes. Influential individual factors have been determined and quantified in this section; household and partner characteristics are now incorporated to address this research question. Household factors of pension wealth, non pension wealth and tenure are the focus of Section 3.5 with partner’s health and employment status considered in Section 3.6.

### 3.5 Household level predictors

There are three household level predictors to incorporate into the analysis and all are related to the financial viability of retirement. The first, tenure, is a time invariant variable which divides women into three groups - those who live in homes that are owned outright, women who have an outstanding mortgage and those who reside in rental properties. The influence of this factor on women’s transitions is considered in the next section. The second covariate is a time varying measure of family pension wealth. Total pension wealth is the amount a couple has accrued from state and private pension sources, and it’s relevance to labour market exit is determined in Section 3.5.2. The third household level measure is for wealth excluding pensions. This includes housing and other property wealth, business value and
non-pension financial resources. Figures are given net of debt. The impact of this measure on transitions is considered in Section 3.5.3. In Section 3.5.4 the effects of women’s health, caring responsibilities and working hours are re-examined for any changes brought about as a result of including these three household measures.

Table 3.6: Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with household level covariates

<table>
<thead>
<tr>
<th>Term</th>
<th>Tenure (1)</th>
<th>Pension wealth (2)</th>
<th>Non pension wealth (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.231</td>
<td>-0.251</td>
<td>-0.265*</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>0.076</td>
<td>0.006</td>
<td>-0.020</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.091</td>
<td>0.131</td>
<td>0.107</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.112</td>
<td>-0.049</td>
<td>-0.030</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.141</td>
<td>-0.150</td>
<td>-0.172</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.042</td>
<td>-0.043</td>
<td>-0.039</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.442**</td>
<td>0.440***</td>
<td>0.464**</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.020</td>
<td>0.199</td>
<td>0.198</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.509***</td>
<td>0.529***</td>
<td>0.568***</td>
</tr>
<tr>
<td>Decline in health (ref: constant health status)</td>
<td>0.409</td>
<td>0.393</td>
<td>0.384</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>1.573***</td>
<td>1.564***</td>
<td>1.529***</td>
</tr>
<tr>
<td>Age:part time</td>
<td>-0.192**</td>
<td>-0.190***</td>
<td>-0.189***</td>
</tr>
<tr>
<td>Tenure (ref: owns home outright)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>-0.295**</td>
<td>-0.289**</td>
<td>-0.268**</td>
</tr>
<tr>
<td>Rents</td>
<td>-0.021</td>
<td>-0.001</td>
<td>0.125</td>
</tr>
<tr>
<td>Household pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>-0.282</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>-0.333*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle quintile</td>
<td>-0.524***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>-0.312*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household non pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>-0.467**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>-0.431**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle quintile</td>
<td>-0.301*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>-0.154</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-4.715***</td>
<td>-4.437***</td>
<td>-4.458***</td>
</tr>
</tbody>
</table>

Observations 6,182  6,182  6,182
Log Likelihood -1,103.495 -1,099.908 -1,100.145
Akaike Inf. Crit. 2,238.990 2,239.816 2,240.291

Note: *p<0.1; **p<0.05; ***p<0.01
3.5.1 Tenure

Tenure is configured as a time invariant measure with women categorised according to their housing status at the time of their first interview for this study. They are assumed to remain in this status as they age. When this variable is incorporated into the final individual level model the deviance decreases by six; this is statistically significant on two degrees of freedom ($\chi^2(2) = 6, p = 0.049787$, Table 3.6, Model 1). Housing status does, therefore, influence women’s transitions out of work - although the relationship differs with the specific type of tenure. This variable is configured with women residing in homes that are owned outright in the baseline category, and the transition rates of renters and women living in mortgaged homes are each compared to the transition rate for this baseline group. Tenants have no significantly different probability of leaving work than women in owned outright homes. The estimated coefficient for renters is -0.021 on the cloglog scale and this transforms to a decrease of only 2.0%.

Having an outstanding mortgage is associated with a lower risk of leaving work and the current model quantifies this as 25.5% less than the risk for women in homes owned outright. However, whilst this difference is statistically significant and large in percentage terms, it does not translate into particularly large differences in estimated hazard rates. At age 51, home owners have a predicted conditional transition probability of 1.0%, whilst for mortgagees it is only 0.3 percentage points lower, at 0.7%. For 55 year olds the estimated values have a difference of less than one percentage point, at 3.1% for owners and 2.3% for mortgage holders; and by age 59 the difference has risen, but only to 2.3 percentage points, with estimated hazards of 9.6% and 7.3% for owners and mortgagees respectively.

Figure 3.7 shows these findings visually, with trajectories in Figure 3.7a plotted on the probability scale and Figure 3.7b on the transformed cloglog scale. The parallel lines of this second figure reflect the proportional hazards assumption, in that the effect of tenure is assumed constant across the age range. The solid line on the upper graph is constructed using the predicted conditional probability of exit for women in homes that are owned outright. The dashed line plots estimated probabilities for women in rental properties - this is virtually indistinguishable from that for owners, reflecting the estimated risk differential of 2.0%. Fitted hazard rates for women in couples with outstanding mortgage obligations are given
Figure 3.7: Predicted women’s employment transition rates according to housing status
by the third line. The vertical distance between this and the other two trajectories reflect the greater impact of mortgages on women’s transition rates.

### 3.5.2 Household pension wealth

The configuration of the pension wealth variable was described in detail in Section 2.6.3.1. It takes a categorical form with women divided into five quintile groups according to the amount of accumulated state and private pension wealth in the household. The wealthiest group forms the reference category. This pension wealth indicator is incorporated into the model that contains the significant individual predictors of health, caring and part time working, and the first household measure of tenure. Parameter estimates and confidence intervals for this model are in Table 3.6, Model 2 on page 123. When each quintile group is considered separately, results suggest that the estimated adjustment to the hazard for women in the middle wealth group is statistically significant at the 1% level, and for the second and fourth groups at the 10% level. These women would be predicted a lower likelihood of leaving work than women from the highest wealth group. However, including this variable in the model does not improve overall model fit ($\chi^2(4) = 7.1734, p = 0.127$) and consequently it is not retained in the household level model.

### 3.5.3 Household non pension wealth

No evidence is found of an association between a couple’s pension wealth quintile and the conditional probability of the female partner exiting employment; here the role that other forms of wealth might have on transition rates is examined. Figures in Table 3.7 show how the transition rate for each quintile group differs between the two wealth variables. There is greater discrepancy between observed transition rates of the wealthiest and poorest quintile in the non pension wealth measure, with a difference of 1.2 percentage points compared to 0.1 for pension wealth. However as per results given in Model 3, Table 3.6 the non pension wealth covariate is not statistically significant ($\chi^2(4) = 6.699, p = 0.1527$). The variation in transition rates of women across the non pension wealth quintiles is not large enough for it to be considered a significant predictor of exit out of work.
Table 3.7: Observed women’s employment transition rates according to pension and non pension wealth quintiles

<table>
<thead>
<tr>
<th>Quintile</th>
<th>Non pension wealth</th>
<th>Pension wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number observed</td>
<td>Number transitions</td>
</tr>
<tr>
<td>Poorest</td>
<td>1059</td>
<td>47</td>
</tr>
<tr>
<td>Second poorest</td>
<td>1297</td>
<td>50</td>
</tr>
<tr>
<td>Middle</td>
<td>1304</td>
<td>57</td>
</tr>
<tr>
<td>Second wealthiest</td>
<td>1279</td>
<td>63</td>
</tr>
<tr>
<td>Wealthiest</td>
<td>1243</td>
<td>70</td>
</tr>
</tbody>
</table>

3.5.4 The influence of household factors - summary

The first research question of this thesis asks whether labour market exit of women in the United Kingdom is influenced by the household context. Family financial resources and their effect on individual level attributes are of primary interest. Two measures of household financial resources - accumulated pension wealth and total non pension wealth - were considered.

We find no statistically significant evidence that the pension wealth quintile of the household impacts on a woman’s chances of staying in work. There is also no evidence that labour market transitions are determined by the level of non pension wealth in the household. A family’s financial situation was found to be relevant through tenure. Women are more likely to remain working if there is an outstanding mortgage on their property compared to those who own outright, but the effect of renting is minimal. As a significant predictor, tenure must be taken into account when considering women’s retirement patterns to facilitate more accurate estimation of individual level attributes.

It was established earlier in Section 3.4 that having a limiting health condition, poor self rated health, deterioration in health and having caring responsibilities are influential for older women’s labour market exit; part time working is also associated with movement out of work. Table 3.8 contains the estimated coefficients and hazard rates for these covariates for both the final version of the individual level model and the household model that has tenure included. Including tenure has the greatest impact on the estimated effect of self rated health and onset of poor health - the predicted conditional probability of a woman leaving work for a woman with poor self rated health rose to 66.4% in the household model compared to
Table 3.8: Risk differential for women’s employment transition estimated by individual and household level models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Individual model</th>
<th>House model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cloglog scale</td>
<td>Probability of exit (%)</td>
</tr>
<tr>
<td>Limiting health</td>
<td>0.216</td>
<td>24.1</td>
</tr>
<tr>
<td>Poor self rated health</td>
<td>0.472</td>
<td>60.3</td>
</tr>
<tr>
<td>Onset health</td>
<td>0.368</td>
<td>44.5</td>
</tr>
<tr>
<td>Caring responsibilities</td>
<td>0.440</td>
<td>55.3</td>
</tr>
<tr>
<td>Part time (main effect)</td>
<td>1.606</td>
<td>398</td>
</tr>
<tr>
<td>Part time (age interaction)</td>
<td>-0.194</td>
<td>-17.6</td>
</tr>
</tbody>
</table>

60.3% in the individual level version. Suffering the onset of a health condition is estimated to increase risk by 50.5%, higher than the 44.5% from the model that excludes tenure. Whilst the impact on other variables of including tenure is minimal, failure to account for it can result in an underestimation of the effect of poor self rated health and the impact of a decline in health status.

3.6 Male partner characteristics

The first research question and hypothesis postulate that male partner characteristics and household pension wealth influence the likelihood of older women’s labour market exit. The results presented in the previous section concentrated on the household aspect of this; now the impact of partner attributes are considered. Specifically, we determine whether partner’s employment status and health are relevant to women’s employment trajectories. First the household level model is adjusted for the control factors of male partner income and age (Table 3.9, Model 1), with indicators for partner’s work status and health following that. Results from incorporating these key employment and health variables are considered in the next two sections.

3.6.1 Partner’s employment status

The spouses and partners of the women studied in this sample are categorized into one of three possible self described employment states. The first group is comprised of employed
Table 3.9: Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, with partner level covariates

<table>
<thead>
<tr>
<th></th>
<th>Partner control variables</th>
<th>Partner’s employment</th>
<th>Partner’s health</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Age</td>
<td>0.283***</td>
<td>0.287***</td>
<td>0.282***</td>
</tr>
<tr>
<td></td>
<td>(0.185,0.380)</td>
<td>(0.189,0.384)</td>
<td>(0.185,0.380)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.232</td>
<td>-0.224</td>
<td>-0.230</td>
</tr>
<tr>
<td></td>
<td>(-0.531,0.067)</td>
<td>(-0.524,0.077)</td>
<td>(-0.529,0.069)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>0.060</td>
<td>0.046</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td>(-0.290,0.411)</td>
<td>(-0.307,0.400)</td>
<td>(-0.288,0.414)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.084</td>
<td>0.081</td>
<td>0.087</td>
</tr>
<tr>
<td></td>
<td>(-0.248,0.417)</td>
<td>(-0.252,0.143)</td>
<td>(-0.246,0.420)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.111</td>
<td>-0.121</td>
<td>-0.122</td>
</tr>
<tr>
<td></td>
<td>(-0.470,0.248)</td>
<td>(-0.482,0.240)</td>
<td>(-0.482,0.237)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.130</td>
<td>-0.135</td>
<td>-0.126</td>
</tr>
<tr>
<td></td>
<td>(-0.445,0.185)</td>
<td>(-0.450,0.181)</td>
<td>(-0.441,0.189)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.039</td>
<td>-0.042</td>
<td>-0.040</td>
</tr>
<tr>
<td></td>
<td>(-0.110,0.032)</td>
<td>(-0.113,0.029)</td>
<td>(-0.111,0.031)</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.435***</td>
<td>0.394***</td>
<td>0.398***</td>
</tr>
<tr>
<td></td>
<td>(0.167,0.702)</td>
<td>(0.121,0.667)</td>
<td>(0.126,0.671)</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.198</td>
<td>0.210</td>
<td>0.184</td>
</tr>
<tr>
<td></td>
<td>(-0.134,0.530)</td>
<td>(-0.122,0.542)</td>
<td>(-0.149,0.516)</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.506***</td>
<td>0.499***</td>
<td>0.495***</td>
</tr>
<tr>
<td></td>
<td>(0.135,0.877)</td>
<td>(0.129,0.870)</td>
<td>(0.124,0.866)</td>
</tr>
<tr>
<td>Decline in health (ref: constant health status)</td>
<td>0.413</td>
<td>0.411</td>
<td>0.409</td>
</tr>
<tr>
<td></td>
<td>(-0.186,1.011)</td>
<td>(-0.189,1.011)</td>
<td>(-0.190,1.008)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>1.568***</td>
<td>1.578***</td>
<td>1.575***</td>
</tr>
<tr>
<td></td>
<td>(0.820,2.316)</td>
<td>(0.829,2.327)</td>
<td>(0.827,2.332)</td>
</tr>
<tr>
<td>Age:part time</td>
<td>-0.191***</td>
<td>-0.194***</td>
<td>-0.192***</td>
</tr>
<tr>
<td></td>
<td>(-0.304,-0.079)</td>
<td>(-0.307,-0.081)</td>
<td>(-0.304,-0.079)</td>
</tr>
<tr>
<td>Tenure (ref: owns home outright)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>-0.266**</td>
<td>-0.239*</td>
<td>-0.260**</td>
</tr>
<tr>
<td></td>
<td>(-0.515,-0.016)</td>
<td>(-0.490,0.012)</td>
<td>(-0.509,-0.010)</td>
</tr>
<tr>
<td>Rents</td>
<td>-0.015</td>
<td>-0.019</td>
<td>-0.060</td>
</tr>
<tr>
<td></td>
<td>(-0.502,0.472)</td>
<td>(-0.512,0.474)</td>
<td>(-0.552,0.431)</td>
</tr>
<tr>
<td>Partner’s age</td>
<td>0.014</td>
<td>0.002</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(-0.010,0.038)</td>
<td>(-0.024,0.028)</td>
<td>(-0.012,0.037)</td>
</tr>
<tr>
<td>Partner’s income (log)</td>
<td>-0.009</td>
<td>-0.001</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(-0.066,0.048)</td>
<td>(-0.060,0.058)</td>
<td>(-0.063,0.051)</td>
</tr>
<tr>
<td>Partner employment status (ref: employed)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>0.403**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.060,0.745)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not working, not retired</td>
<td>0.201</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.229,0.630)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Partner has limiting health (ref: no limitation)</td>
<td></td>
<td></td>
<td>0.201</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-0.069,0.472)</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.439***</td>
<td>-4.856***</td>
<td>-5.413***</td>
</tr>
</tbody>
</table>

Observations 6,182 6,182 6,182
Log Likelihood -1,102.822 -1,100.163 -1,101.785

Note: *p<0.1; **p<0.05; ***p<0.01
men, the second those that report as retired and the third is an amalgamation of the long term sick or disabled, unemployed and those caring for home and family. This third group is collectively referred to as ‘not working, not retired’. The employed partners are the designated reference category and the transition rates of the other two groups will be compared with this one.

This partner employment indicator is added in to the household level model that has also been adjusted for partner’s age and income. Results are given in Table 3.9, Model 2. The log likelihood test indicates that the coefficients of this variable are statistically different from zero ($\chi^2(2) = 6, p = 0.05$); this provides sufficient evidence to conclude that male partner’s employment status does influence the probability of a woman transitioning from work. Compared to women with employed partners, those coupled to retired men are 49.6% more likely to exit. A male partner who is in an alternative not working, not retired state also raises the risk of transition; this effect is quantified as 22.3%.

There are three different visual representations of partner’s employment status superimposed on the observed values in Figure 3.8a. The solid line shows the predicted trajectory for a woman partnered to a man who remains in work for the duration of this time span; that is, from when the woman is aged 50 until age 59. This version of the fitted model closely predicts the observed transition rates for these women, which are plotted as solid circles (●); there is minimal difference between the predicted rates of the trajectory and those from the observed sample data. Transition rates for women coupled to non-employed men are not predicted as accurately as those for women with employed partners. The hazard for women aged 53 and partnered to a retired man is overestimated with that for 58 year old women underestimated. The dashed line and crosses represent the fitted trajectory and observed values for these women, with the dashed line and triangles plotting them for women partnered to not-working, not-retired men. The model predicts transition rates more accurately between the ages of 53 and 56 for these women; it over predicts when younger than this and has particularly large deviance for older women. Further improving the fit of the model requires incorporating interaction terms with age that would better capture the changing impact of men’s employment status over time, but this would result in a prohibitively complex model.
Figure 3.8: Observed and predicted women’s employment transition rates for partner’s employment status
3.6.2 Partner’s limiting health

A binary indicator for partner’s limiting health status is incorporated into the household model. This variable takes the same structure as for women’s limiting health; men with no limiting health condition are coded as the reference group. Results are given in Table 3.9, Model 3. Deviance statistics indicate that partner’s limiting health is not a significant predictor of women’s transitions ($\chi^2(1) = 2, p = 0.1498$). This suggests that women partnered to men with a limiting health condition have a similar level of transition risk as those coupled to healthy men; this finding is discussed in more detail in Section 3.7.3.

3.6.3 Have partner covariates modified individual effects?

Including the male partner covariates may result in changes to the estimated effects that a woman’s individual health status, caring responsibilities and working hours have on her chances of continued employment. Male partner characteristics were incorporated into the analysis in two stages, with their age and income entered first as control variables and employment status following that. Table 3.10 (page 133) contains the estimated coefficients for women’s individual level variables of interest. In the first two columns they are given for the household model before male partner attributes were included. They are also shown for the model that controls for partner age and income and, in the far columns, with the addition of partner’s employment status.

The coefficients for the health indicators show minimal difference across the three specifications. The probability of a woman leaving work if she has a limiting health condition is estimated at 22.4% in the household model and 23.4% in the final partner model. The figures from these same two models for a woman with poor self rated health are estimated at 66.4% and 64.7% respectively, and for the onset of a health condition they are 50.5% and 50.8%. Estimated hazard rates for part time workers also show little change with the addition of partner level variables. The likelihood of transitioning that is associated with having caring responsibilities, however, does change when partner characteristics are taken into account. In the household level model - prior to any partner variables being added in - the effect of caring was estimated at 55.6%. This decreased slightly to 54.5% after partner’s age and in-
<table>
<thead>
<tr>
<th>Variable</th>
<th>Household model</th>
<th>+ Male partner age &amp; income</th>
<th>+ Male partner employment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cloglog scale</td>
<td>Probability of exit (%)</td>
<td>Cloglog scale</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Limiting health</td>
<td>0.202</td>
<td>22.4</td>
<td>0.198</td>
</tr>
<tr>
<td>Poor self rated</td>
<td>0.509</td>
<td>66.4</td>
<td>0.506</td>
</tr>
<tr>
<td>Onset health</td>
<td>0.409</td>
<td>50.5</td>
<td>0.413</td>
</tr>
<tr>
<td>Caring responsibilities</td>
<td>0.442</td>
<td>55.6</td>
<td>0.435</td>
</tr>
<tr>
<td>Part time (main effect)</td>
<td>1.573</td>
<td>382</td>
<td>1.568</td>
</tr>
<tr>
<td>Part time (age interaction)</td>
<td>-0.192</td>
<td>-17.5</td>
<td>-0.191</td>
</tr>
</tbody>
</table>

Table 3.10: Risk differential for women’s employment transitions estimated by household and partner models for individual level covariates
come were incorporated, whilst adjusting for partner’s employment status caused a greater decrease with an estimate of 48.3%.

The findings presented here indicate that male partner’s employment status does directly influence older women’s labour market exit with those coupled to employed men having the lowest predicted risk of transition. It follows that if this variable were omitted from the model the underlying sample would become biased towards women partnered with employed men, as those partnered to higher risk non-working men leave the sample at younger ages. Over time, the composition of the women’s risk set will change and include a greater proportion of dual-employed households. However, as detailed above, the estimated effects of women’s health and working hours remain constant irrespective of the inclusion of partner variables in the model, but the effect of having caring responsibilities does change. This suggests that in the underlying sample, the proportion of women with health issues or part time working is independent of partner’s employment status. If models of women’s retirement were not adjusted for partner’s employment status the impact of having caring duties, however, could be overestimated.

3.7 Diagnostics

In this section diagnostic measures relating to the final event history model for predicting women’s transitions are presented. This model includes indicators for health, part time working, tenure and male partner’s employment status, along with control measures for income, social class and education with coefficients as listed in Table 3.9, Model 2, page 129. The aim of these diagnostic measures is to summarise the overall fit of the model, detect cases that are poorly predicted, identify influential observations and quantify the impact of these observations on model estimates. The first two of these objectives are achieved through analysis of deviance residuals as explained in Section 3.7.1. Leverage and deletion diagnostics - that relate to the impact of particular observations - are the subject of Section 3.7.2.
3.7.1 Goodness of fit

Goodness of fit measures summarise how well a given model predicts the outcome of interest which, in this case, is the conditional probability that a woman transitions from work at a given age. Of interest is a measure of how well the model predicts employment exit for each respondent overall rather than for one specific period of time. The deviance residual is one measure of fit that can be easily aggregated from person-period to person level. The person-period level deviance residuals from the final fitted model for woman \( i \) at age \( t \) are calculated from Equation 3.3 (Singer and Willett, 2003); residuals take a positive value at ages where a transition has occurred and are negative otherwise. The sum of the square of each person-period residual gives an aggregate person level measure of model fit.

\[
\text{Deviance}_{it} = \begin{cases} 
-\sqrt{-2\log(1 - \hat{h}_{it})}, & \text{if no transition occurs} \\
\sqrt{-2\log(\hat{h}_{it})}, & \text{if transition occurs}
\end{cases} \tag{3.3}
\]

The calculated deviance residuals are plotted in Figure 3.9 on page 136. Person-period residuals are in the upper graph, whilst in the lower are aggregate values for each woman. Note that the high values of the person-period deviance residuals - most for the transitioned population are above two in Figure 3.9a - reflect relatively low predicted hazard rates. Predicted hazard rates - that is the value of \( \hat{h}_{it} \) in Equation 3.3 - are bound between 0 and 1. A value that is closer to 0 will give a higher value of \(-2\log(\hat{h}_{it})\) and therefore higher deviance residual. Estimated hazards closer to 1 give a low value of \(-2\log(\hat{h}_{it})\) and lower deviance residual. The six cases labelled in the figure have the largest residuals; however these are not sufficiently different from those of other cases to be of concern, and these cases have no common observed attribute to suggest that the model performs poorly for any particular category of woman.

The deviance residuals examined here provide one summary measure of model fit. There are other types of residual available for binary outcome models (Pregibon, 1981; Agresti, 2013) however their application to discrete time event history models is not necessarily straightforward as they may need to be adapted to account for censored or truncated observations that are present in event history models. Additionally - as in the deviance case -
Figure 3.9: Deviance residual plots for event history model of women’s transition from employment
residuals may be more informative if calculated on an aggregate person rather than person-period level, but methods for achieving this are not widely addressed in the literature. Given these constraints, we limit the residual analysis here to the deviance measure.

### 3.7.2 Influential cases

The two diagnostic measures presented in this section detect observations that may have a significant impact on model fit. The first are leverage values calculated from the hat matrix and the second are dfbetas, which are a standardised measure of the influence that an observation has on the estimate of a given coefficient.

#### 3.7.2.1 Detecting influential cases: leverage

A measure of the potential influence of each observation on parameter estimates is obtained from the estimated hat matrix. Agresti (2013) defines the estimated hat matrix for a logistic regression model as

\[
\hat{H} = \hat{W}^{1/2}X(XX')^{-1}X'\hat{W}^{1/2}
\]  

(3.4)

where \(X\) is the \(J \times (p + 1)\) design matrix containing values for each of the \(J\) covariate patterns formed by the observed values of \(p\) model covariates. The weight matrix \(\hat{W}\) is \(J \times J\) diagonal with element \(\hat{w}_{jj} = n_j\hat{\pi}(x_j)[1 - \hat{\pi}(x_j)]\) where \(n_j\) denotes the total number of observations with the same covariate pattern.

For the model studied here the number of covariate patterns is equal to the number of person-period units in the sample dataset; that is, \(J = 6182\) and \(n_j = 1\forall j = 1, 2...6182\). This is because the income variable is entered in continuous form, and because of the inclusion of time varying predictors. These two factors have, to an extent, contributed to each individual person-period unit having a unique combination of covariate values. The diagonal elements of \(\hat{H}\) give the leverage values, and because they are calculated on a person-period basis, each indicates the potential influence on parameter estimates that a woman has at each time point that she contributes to the dataset. Leverage values fall between 0 and 1 and sum to the number of parameters in the model.

The leverages for the final model for women’s transitions are shown visually in Fig-
Figure 3.10 plots leverage for each person-period unit, and to aid exposition the values for four sample women are highlighted. These four individuals are selected because they contribute the five periods with the highest leverage. All other observations from each of these four women are also identified by label and colour such that the observations plotted in orange belong to individual A, with those in red, green and blue belonging to respondents B, C and D respectively. The point to note here is that the influence of a woman’s covariate values can change from one observation to the next. Consider women A, B and C; each of these individuals has one specific observation that has a relatively high potential influence, whilst their remaining observations all have very low leverage. In contrast, woman D has four distinctly different leverage measurements. This variation in leverage within respondents is likely a consequence of time varying covariates. Leverage incorporates information about where an observation is positioned in the covariate space, but with time varying measures this position could change, as the recorded value of some predictors is altered in response to changes in women’s health or financial resources, for example.

Figure 3.10b graphs leverage against the predicted probability of a transition occurring, again on a person-period level. This plot shows a positive relationship between the estimated hazard and leverage with higher predicted transition probabilities associated with higher leverage. Important here, however, is the magnitude of the leverages; few are above 0.05. This indicates that each individual period of observation has minimal influence of parameter estimates, and this would likely also be the case if some form of aggregate person level leverage measure was calculated. Deriving such an aggregate value would involve combining leverages for the different covariate patterns that are observed within each woman, but given the small magnitude of the person-period values this is unlikely to result in any different conclusion from that gained from the person-period level statistics. The conclusion from this particular diagnostic is, therefore, that no particular case in the sample has an undue influence on the fit of the model.

3.7.2.2 Deletion diagnostics: dfbetas

The dfbetas indicator is a deletion diagnostic in that it measures the change in a given coefficient if a particular observation was removed from the sample. Dfbetas are calculated here
Figure 3.10: Leverage plots from final logistic regression model for predicting women’s employment transitions
for the continuous variables of women’s and male partner income, on a person-period basis. Women can have a different dfbetas value for each period. Figure 3.11a plots these for the income covariate against the predicted hazard. Six women - labelled with case numbers - have values that are high relative to the rest of the sample. Note that none of these six have more than one higher value; their greater influence on the income coefficient is limited to one observed time point and not at each age for which they are observed. A second point to note is the six influential cases are spread across the range of predicted probabilities - women of low, medium and high risk of exit have a higher influence on the income coefficient.

The dfbetas for the male partner income covariate are plotted against the estimated hazard in Figure 3.11b. There are nine observations that have a high impact on the coefficient for partner income, relative to the rest of the sample. Again, these are single observations for the indicated cases with no respondent having more than one influential period. In this instance, however, the observations that have the greatest influence on the estimated effect for male partner income tend to be women with low risk of exit.

Note that, whilst this inspection of deletion diagnostics has identified some influential person-period level observations, there is limited literature available that considers the aggregation of these values to obtain an overall measure of influence for each sample member. Additionally the application of these measures to event history models, as opposed to logistic regression, is not widely addressed, but further investigation of these issues falls outside the remit of this thesis.

### 3.7.3 Summary

This section has examined three diagnostic measures for the event history model that predicts the conditional probability of older women’s transitions out of work. A measure for goodness of fit was provided by the deviance residuals with the influence of specific cases indicated by leverage and dfbetas values. The deviance residuals show there is no particular observation for whom the model performs poorly, whilst the leverage statistics indicate no one case has an undue influence on model fit. The dfbetas deletion diagnostic was calculated for women’s and male partner income covariates. These values show that the observations with the greatest impact on the income coefficient are from women with diverse risk profiles - that
●

DFBetas

0.25

0.00

4018

●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
● ●
●
●
●●
●
● ●● ●● ● ●●
●
●
●●
●
●
●
● ●●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
● ● ●●
●
●
●
●
●
●
●
●
●
●
●●
● ● ●
●
●
● ● ●●● ● ●
●
●●●● ●
●
●
●
● ●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●●
●
●●
●●●
● ●
●
●
●●
●
●
● ●
●
●
●●
●
●
●
●
●
●
● ●●●●●● ●
●●
●
●
●
●●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●●
●● ●●
●
●●
●
●
●
●
●
●
●●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●●●
●
●
●
●
●
●
●
●
●
●●
●
●●
●●●●
●
●
●
●
●
●
●
●
●
●●●●
●
●
●
●●●●
●●●
●●●●
●●●
●
●
●●
●
●
●
●
●
●
●
●
●
●●●
●
●
●
●
●
●
●●
●
●
●●●
●
●
●
●●
●●●
●
●●●●
●●
●
●●●●
●●●
●●
●
●
●
●●●
●●
●
●
●
●●●●●
●●
●●●●
●
●
●●●
●●
●●
●●●
●
●●
●
●●
●
●
●
●
●
●
●
●●●
●●
●●●●
●
●
●●●
●●●
●
●
●
●
●●●
●●
●
●
●●●●●●
●
●●
●
●●
●
●
●●●
●
●
●
●
●●●
●●●●●●
●
●
●●
●●●●●
●
●●
●●
●●●
●●
●●
●
●
●
●●●●
●
●
●
●●
●
●
●
●●
●●●
●
●
●
●
●●●●
●
●
●
●
●
●
●
●
●
●
●●●
●●●●●
●
●●
●●●
●
●
●
●
●●
●●
●
●
●●
●●●
●
●
●●
●
●●●
●
●
●●
●
●
●
●
●
●●
●●●●●
●
●
●●●
●
●
●
●
●
●●
●●●●
●
●
●●●
●
●●
●●●
●
●
●●
●
●●
●●
●●●
●●●●●
●
●●
●
●●
●
●
●●
●●
●
●●●
●
●
●
●●●●
●
●●●●
●
●
●
●
●
●
●●
●
●
●
●
●●●
●
●
●
●
●●●
●●●●
●
●
●●
●
●
●
●
●
●
●
●
●●●●
●●
●●
●
●
●●●●
●●
●
●
●
●
●●
●
●●
●
●
●
●
●
●
●●
●
●
●
●●
●●
●
● ● ●● ●● ●
●●
●
●
●
●
●●
●
●
●
●●
●
●●●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●●
●
●
●
●
●
●
●
●
●●●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●●●
●
●
●
●
●
●
●
●
●
●
●
● ●●
● ●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●●
●
●
●
●
●●●●
●
●
●
●●
●
●
●●
●
●
●
●●
●
●●● ●●
●
●
●●
●
● ●●●●●
●
●
●
● ●●● ●●
●●
●●●
●● ●
●●●
●●
●
●
●●
● ●● ●● ●
● ●●
●
●
● ●
●
●
●● ●
●
●
●●
●

●

●

●
●

●●
●

●
●

−0.25
●

1223
●
● 5632 ●

5999

4078
●

2540

−0.50
0.0

0.1
0.2
Predicted conditional probability of women's employment transition

0.3

(a) DFBetas plot vs predicted probability for women’s income

0.25

DFBetas

●

0.00

●
●
●
●
●
●●● ●
●
●●●
●
● ●
● ●● ●● ●
● ●●●●●●
●● ●
●●●
●
●
●
●
●
● ●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●●
● ●
●
●● ●
●
●●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
● ●
●
●
●
●
●●
●
●●
● ●
●●●
●
●●
●
●
●
●
●
●●
●
●
●●●
●●
●
●
●
●●
●
●
●
●●
●
● ●● ●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●●●
●
●
●
●
●
●
●
●
●●●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●●
●
●
●
●
●
●●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●●
●
●●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●●
●
●
●
●●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●●
●
●
●●
●
●
●
●
●●●●
●
●●●●
●
●
●
●●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●●
●
●●●
●
●
●
●
●●●
●
●
●●
●
●
●●●
●
●
●
●
●
●
●
●●
●
●●
●
●●●
●●●
●
●
●●●
●●
●●●●
●
●
●
●●●
●
●
●
●●
●●
●
●
●
●●●
●
●
●
●●
●
●
●●
●●
●
●●
●
●
●
●
●
●●
●
●●●●●
●●
●●
●
●
●
●
●●
●
●●
●●●●
●●●●
●
●●●●
●●●
●
●
●
●●●
●
●
●
●
●
●
●
●
●●●
●●●
●
●●
●
●●●
●●●●●●
●
●
●●
●●
●●●
●
●●●●
●
●
●●
●
●●●
●●
●●
●
●
●
●●
●
●
●
●●
●●●●
●
●
●●
●
●
●●
●●●
●
●
●●
●
●
●●●
●
●●
●
●
●
●●●
●●●●●
●●●●
●●
●●●●●●
●●●●
●
●
●
●
●
●●
●
●●●
●●
●
●
●
●
●●
●
●
●
●
●
●●●●●
●
●●
●
●●●●
●
●●
●●●
●
●
●
●
●
●
●
●●●●●
●
●
●
●
●
●
●
●●●
●●
●
●
●●●
●
●●●●
●
●
●●●
●
●●●●
●●
●
●●
●
●
●
●
●●●
●
●●●●
●●●●●
●●●●
●●
●●●
●
●
●●●●
●●●●
●
●
●
●
●
●
●●●
●
●
●●
●
●
●
●●●●
●
●●●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●●●
●
●
●●●●
●
●
●
●
●●
●
●
●
●●
●●
●
●
●
●●
●
●
●
●
●
●
●●
●●
●
●●
●
●
●●
●
●
●
●
●
●
●
●
●●
●
●●
●
●
●●●
●
●
●●
●●
●
●
●
●●●
●
●
●
●
●
●
●
●●
●
●●
●
●
●
●
●
●
●●
●
●
●
●
●
●●
●
●
●
●●
●
●
●
●●
●●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
● ●●●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●●●
●●●
● ●●
●●
●● ● ●● ●●● ●●● ●
●
●
●●
●
●
●
●
●●●● ●●
●●●
●
●
●
●
●
●●●● ●●
●●
● ●●●●●
● ● ● ● ●
●
●●
●●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
●
● ●●
●
● ● ● ●
●
●
●
●
●
●
●
●
●

●●

●
●

●

●
●

●

●

−0.25

●
●
●
●
●

●

●
●
●

●

5955
3986 ●
● ●

3696 ●5663

5933
2964
●
6067

●

● 1805

5999 ●

−0.50
0.0

0.1
0.2
Predicted conditional probability of women's employment transition

0.3

(b) DFBetas plot vs predicted probability for male partner’s income

Figure 3.11: DFBetas against predicted conditional probability of women’s transition for
income covariates

141


is, they are a mix of low, medium and high risk observations - whereas it is those with lower risk of exit that influence the male partner income coefficient. Removing these cases from the sample would disproportionately impact on the sub population of low risk women.

The diagnostic measures summarised here were each calculated on a person period basis with values given for each year of age for which a woman was included in the risk set. Calculating values at this measurement level shows how model fit can vary within each woman’s observation set; the fitted model does not necessarily predict the probability of employment exit equally well across all time points for any given respondent. Similarly the influence that a woman’s observations have on model fit and parameter estimates can vary for each of her observation periods. From this analysis, however, the model appears to predict adequately for all cases and there is no strong evidence to suggest any one has a disproportionate effect on the results.

3.8 Random effects model

The fixed effects models estimated up until this point assume that the included covariates capture all heterogeneity in the hazard (Narendranathan and Stewart, 1993). However this is unlikely to be the case; additional characteristics that impact on a woman’s chances of staying in work are probable, but not observed. A random effect, $u_i \sim N(0, \sigma^2)$, was specified in Equation 3.2 and is incorporated to account for unobserved time invariant individual differences. The motivation for this is further developed below with results of the fitted random effect model following that.

3.8.1 Rationale for fitting a random effect model

Failing to account for unobserved time invariant characteristics can result in inaccurate estimates of the relationship between observed covariates and the hazard, and underestimation of the age effect (Yamaguchi, 1991). The mechanism behind this is explained with reference to Figure 3.12. In this figure there are five hypothetical women, A - E. Each line plots the conditional probability that the woman leaves work for the given year of age, until she either exits or reaches age 59. Woman A has a high risk profile with the greatest propensity to
leave work. Woman E has the lowest risk profile. Assume that this heterogeneity persists after all relevant observed factors have been taken in to account. Woman A, therefore, has a combination of unobserved factors that are causing her to have a higher likelihood of leaving work. In the context of this analysis such factors that could lead to a higher risk of transition include lower job satisfaction or long periods of time out of work prior to the age of 50, for example. Women D and E have a combination of these factors that lead to low risk of transition and have subsequently longer employment spells.

Now consider what happens to the composition of the risk set over time, and the relationship between this and the estimates for the factors that are included in the model. At age 50 the risk set is comprised of all five women and estimates of the observed factors are based on the transition rates for the entire group. However the risk set for 54 year old women consists of only Women C, D and E - because of the higher risk associated with their unobserved factors, Women A and B transitioned out of work and are no longer considered in the modelling process. Estimates of coefficients for the observed factors, therefore, are based on a risk set of only three women who have lower risk profiles. Women still in employment at older ages are those with low hazard rates, because respondents with higher risk are ‘selected out’ early due to the influence of unobserved factors. The estimated relationship between age and the hazard rate, therefore, is lower than it would be if there were no such unobserved factors operating on the sample.

Figure 3.12: Sample selection effect
The effects of other included predictors - women’s health, caring, working hours, tenure and partner’s employment status - in the current single level version of the model are also potentially misspecified. Coefficients from a multilevel model will likely have a greater magnitude after the random effect is introduced; incorporating the additional term increases the residual variance and therefore the absolute value of the estimated coefficients. The interpretation of these coefficients from the multilevel model will also change from that of the single level model. This will be explained further in Section 3.9 after the results of the multilevel specification are obtained.

### 3.8.2 Results

Coefficients and 95% confidence intervals from this multilevel model are in Table 3.11 alongside those from the previous single level version which did not account for unobserved factors. The likelihood ratio test rejects a null hypothesis of \( \sigma_u = 0 \) (\( \chi^2(1) = 22.8, p < 0.01 \)) and this supports the inclusion of the adjustment for unobserved heterogeneity. Additionally, covariates that were non-significant for the prediction of women’s exit in the single level model - specifically the pension wealth, non pension wealth and male partner health variables - were also added to the random effect model to reassess their impact. The pension wealth indicator was again not significant (\( \chi^2(4) = 4.6956, p = 0.32 \)) and neither was that for non pension wealth (\( \chi^2(4) = 3.1898, p = 0.5266 \)). Male partner health is also not significant (\( \chi^2(1) = 0.4728, p = 0.4917 \)) as it was for the single level model. All three variables therefore remain out of this model.

Estimated effects for age, health, caring, partner’s employment status and tenure from the random intercept and single level models are extracted from Table 3.11 and summarized in Table 3.12. The first two columns in this table contain the estimated coefficients and the third and fourth give the predicted percentage increase or decrease in hazard for each of the two specifications. This is obtained from the exponentiated coefficient. There are two interpretations of coefficients from the random effect model. They differ according to whether the covariate in question entered the model in a time varying or time invariant form. This will be explained further, and each of these groups of predictors discussed in turn, after consideration of the age effect in the two models.
Table 3.11: Parameter estimates from single level discrete time event history model and random intercept model, for the conditional probability of women’s transition from employment

<table>
<thead>
<tr>
<th></th>
<th>Single level model</th>
<th>With random intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Age</td>
<td>0.287***</td>
<td>0.362***</td>
</tr>
<tr>
<td></td>
<td>(0.189,0.384)</td>
<td>(0.246,0.478)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.224</td>
<td>-0.339*</td>
</tr>
<tr>
<td></td>
<td>(-0.524,0.077)</td>
<td>(-0.727,0.050)</td>
</tr>
<tr>
<td>A level equivalent</td>
<td>0.046</td>
<td>-0.071</td>
</tr>
<tr>
<td></td>
<td>(-0.307,0.400)</td>
<td>(-0.531,0.388)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.081</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(-0.252,0.413)</td>
<td>(-0.431,0.430)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.121</td>
<td>-0.246</td>
</tr>
<tr>
<td></td>
<td>(-0.482,0.240)</td>
<td>(-0.703,0.211)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.135</td>
<td>-0.190</td>
</tr>
<tr>
<td></td>
<td>(-0.450,0.181)</td>
<td>(-0.607,0.227)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.042</td>
<td>-0.052</td>
</tr>
<tr>
<td></td>
<td>(-0.113,0.029)</td>
<td>(-0.143,0.040)</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.394***</td>
<td>0.486***</td>
</tr>
<tr>
<td></td>
<td>(0.121,0.667)</td>
<td>(0.149,0.823)</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.210</td>
<td>0.228</td>
</tr>
<tr>
<td></td>
<td>(-0.122,0.542)</td>
<td>(-0.189,0.645)</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.499***</td>
<td>0.556**</td>
</tr>
<tr>
<td></td>
<td>(0.129,0.870)</td>
<td>(0.095,1.017)</td>
</tr>
<tr>
<td>Decline in health (ref: constant health status)</td>
<td>0.411</td>
<td>0.456</td>
</tr>
<tr>
<td></td>
<td>(-0.189,1.011)</td>
<td>(-0.247,1.158)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>1.578***</td>
<td>1.573***</td>
</tr>
<tr>
<td></td>
<td>(0.829,2.327)</td>
<td>(0.722,2.424)</td>
</tr>
<tr>
<td>Age:part time</td>
<td>-0.194***</td>
<td>-0.183***</td>
</tr>
<tr>
<td></td>
<td>(-0.307,-0.081)</td>
<td>(-0.312,-0.054)</td>
</tr>
<tr>
<td>Tenure (ref: owns home outright)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>-0.239*</td>
<td>-0.374**</td>
</tr>
<tr>
<td></td>
<td>(-0.490,0.012)</td>
<td>(-0.703,-0.044)</td>
</tr>
<tr>
<td>Rents</td>
<td>-0.019</td>
<td>-0.184</td>
</tr>
<tr>
<td></td>
<td>(-0.512,0.474)</td>
<td>(-0.843,0.476)</td>
</tr>
<tr>
<td>Partner’s age</td>
<td>0.002</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(-0.024,0.028)</td>
<td>(-0.037,0.032)</td>
</tr>
<tr>
<td>Partner’s income (log)</td>
<td>-0.001</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td>(-0.060,0.058)</td>
<td>(-0.080,0.061)</td>
</tr>
<tr>
<td>Partner employment status (ref: employed)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>0.403**</td>
<td>0.456**</td>
</tr>
<tr>
<td></td>
<td>(0.060,0.745)</td>
<td>(0.018,0.894)</td>
</tr>
<tr>
<td>Not working, not retired</td>
<td>0.201</td>
<td>0.170</td>
</tr>
<tr>
<td></td>
<td>(-0.229,0.630)</td>
<td>(-0.381,0.721)</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.856***</td>
<td>-5.446***</td>
</tr>
<tr>
<td></td>
<td>(-6.501,-3.210)</td>
<td>(-7.606,-3.286)</td>
</tr>
</tbody>
</table>

Random effect

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>6,182</td>
</tr>
<tr>
<td>Number of women</td>
<td>1569</td>
</tr>
<tr>
<td>Intercept standard deviation</td>
<td>1.485</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-1.100.163</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>2,240.326</td>
</tr>
<tr>
<td>Bayesian Inf. Crit.</td>
<td>2,360.808</td>
</tr>
</tbody>
</table>

*Note: *p<0.1; **p<0.05; ***p<0.01
Table 3.12: Comparison of estimated effects from single level and random intercept event history models for women’s transition

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Estimated coefficient</th>
<th>Change in hazard (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single level</td>
<td>Random intercept</td>
</tr>
<tr>
<td>Age</td>
<td>0.287</td>
<td>0.362</td>
</tr>
<tr>
<td>Caring</td>
<td>0.394</td>
<td>0.486</td>
</tr>
<tr>
<td>Limiting health</td>
<td>0.210</td>
<td>0.228</td>
</tr>
<tr>
<td>Poor self rated health</td>
<td>0.499</td>
<td>0.556</td>
</tr>
<tr>
<td>Onset health</td>
<td>0.411</td>
<td>0.456</td>
</tr>
<tr>
<td>Part time (main effect)</td>
<td>1.578</td>
<td>1.573</td>
</tr>
<tr>
<td>Part time (age interaction)</td>
<td>-0.194</td>
<td>-0.183</td>
</tr>
<tr>
<td>Partner retired</td>
<td>0.403</td>
<td>0.456</td>
</tr>
<tr>
<td>Partner not working nor retired</td>
<td>0.201</td>
<td>0.170</td>
</tr>
<tr>
<td>Mortgage</td>
<td>-0.239</td>
<td>-0.374</td>
</tr>
<tr>
<td>Rent</td>
<td>-0.019</td>
<td>-0.184</td>
</tr>
</tbody>
</table>

A measure of duration dependence - that is, the relationship between age and the hazard - is given by the coefficient for age in the fitted model. As discussed earlier, this is underestimated in the single level model and we expect it to increase in magnitude in the random intercept version. This is confirmed by the figures in the first row of Table 3.12; the age effect has changed from 0.287 in the single level model to 0.362 in the multilevel specification. These coefficients translate to 33.2% and 43.6% on the probability scale, respectively. In the single level model a woman’s risk of leaving work was predicted to increase by 33.2% per year of age after 50. This is now 43.6% after the random effect adjustment for unobserved factors.

The time varying covariates that are of primary interest represent health, caring responsibilities and partner’s employment status. The coefficients for these variables in Table 3.12 give the estimated change in hazard for a woman with the given attribute from what it would be if she did not have that characteristic. The coefficient of caring from the random effect model is 0.486, and this translates to an increase in risk of 62.6% for a woman with caring responsibilities compared to what it would be if she did not have caring duties. In the single level model this coefficient was estimated at 0.394 or only 48.3%.

The impact of having a limiting health condition on the hazard shows minimal change...
between the two specifications. In the single level model it was estimated at 23.4% higher for a woman with such a condition compared to if she had no health limitation; now, in the multilevel version, having a health problem raises the risk by 25.6%. The coefficients for the other two health variables, of self rated health and deterioration in health, change with the addition of the random intercept term. A woman with poor self rated health is now predicted a 74.4% higher risk of leaving work, ten points higher than the 64.7% increase predicted from the single level model. The predicted probability of transitioning associated with the onset of a health condition has risen from 50.8% in the single level specification to 57.8% in the multilevel model. Both the main effect and age interaction term of part time working are similar across both specifications.

A woman with a retired spouse or partner has a 57.8% higher probability of leaving work than if he was employed. This is approximately eight percentage points higher than the hazard predicted by the single level model. However the effect of having a partner who is not in work but also not retired - that is, with an unemployed, sick or disabled or caring status - is estimated lower in the random intercept model. The risk differential is now 18.5% rather than 22.2%.

The interpretation of time invariant factors from the random effects model is different to that of time varying predictors. Time varying covariates are a combination of within and between individual effects, whilst coefficients for time invariant measures give between subject effects only. Estimates for time invariant measures therefore give the difference in risk for two separate women who have different values of the covariate in question. All other factors, including the random effect, are identical for these two women. This means that they have the same levels of observed predictors and are assumed the same risk profile for unobserved factors. In the case of the tenure measure, the multilevel model predicts a woman from a household with an outstanding mortgage is 31.2% less likely to leave work than a woman in a home that is owned outright, if it is assumed that the influence of unobserved factors on the hazard is the same for each of these women.
3.9 Interpretation and contribution of results

Recent research into women’s later life employment patterns is focused on the domestic context and considers the interaction between women’s attributes, those of her partner and joint household characteristics (Loretto and Vickerstaff, 2013; Duberley et al., 2014). However these studies are primarily qualitative in nature and, whilst the conclusions inform with regards to the factors that can influence women’s retirement, they are not generalisable to the wider population. They also offer limited insight into the magnitude and relative importance that each factor might have on the chances of an older woman remaining in work. Limitations also apply to the findings from available survey based research; existing models of couples’ retirement behaviour are primarily based on American datasets (Phillipson and Smith, 2005) and are not necessarily applicable to the United Kingdom. This analysis advances current understanding by using data from the English Longitudinal Study of Ageing to identify factors relevant to women’s labour market exit between the ages of 50 and state pension age. The effect that each has is quantified with the impact of key variables permitted to vary across the studied age range. We are able to ascertain the most influential factors, and also how a particular effect might become more or less influential as women grow older and approach state pension age.

3.9.1 Identifying significant predictors of older women’s employment transitions

Limiting health conditions, poor self rated health and a deterioration in health status are established as significant predictors associated with older women’s labour market exit prior to state pension age, as are having caring responsibilities and part time working hours. The impact of health effects or caring responsibilities were not found to vary over time with the increase in risk associated with these attributes remaining constant between the ages of 51 and 59. Part time workers, however, were found to have an increasing likelihood of leaving work as they age. Tenure also predicts transition, as does the partner’s employment situation. There is no evidence, however, of any difference in the probability of early exit between women from different pension wealth quintile groups.
Previous evidence of an association between family financial resources and women’s employment is limited; Szinovacz and Deviney (2000) and Loretto and Vickerstaff (2013) contend that older women’s labour market participation is responsive to family income with women working for as long as is necessary to ensure the couple’s economic wellbeing. The results found in this thesis suggest that women’s employment is not adjusted in response to the level of pension wealth held by the couple, with their conditional probability of employment exit independent of their accrued pension resources. There is also no statistically significant difference in transition rates between women from non-pension wealth quintile groups. Women with partners who have a limiting health condition are not found to have any significantly higher or lower chance of leaving work compared to those with healthy partners, once socioeconomic and caring effects are controlled for. Prior to this research the factors listed here were identified from qualitative research participants as being relevant to labour force engagement (Loretto and Vickerstaff, 2013; Duberley et al., 2014). The conclusions arising from this thesis are based on analysis of large scale survey data and thus contribute statistically rigorous support and generalizable findings.

3.9.2 Measuring and ranking the impact of predictors

Identifying the attributes that are or are not significant predictors of older women’s labour market transitions is one benefit of using event history methods as applied here. Another is that the impact of each of the significant predictors is quantified and, consequently, we can establish the relative importance of each factor. The most influential is poor self rated health, which raises the risk of leaving work by an estimated 74.4%. Having caring responsibilities also has a high impact - the probability of leaving work prior to state pension age if a woman provides care is 62.6% higher than if she did not. The next two factors in terms of magnitude of influence are suffering a deterioration in health and having a retired partner. These each increase the likelihood of leaving work by 57.8% compared to if a woman remained in good health or had a working partner.

The remaining significant predictors each have a markedly lower impact on the hazard. Having a mortgage is associated with a reduced probability of staying in work with an estimated effect of 31.2% and the third health measure, of limiting health, increases risk by an
average of 25.6%. This is notably less than the effect of the self rated health and deterioration in health predictors. Of all the significant predictors having a partner who is not working but also not retired, and residing in a rental property have the lowest impact on the chances of continued employment. A woman partnered to a man who is out of work in an unemployed, caring or illness state is estimated to have an 18.5% higher probability of transitioning early. The renting factor is similar in magnitude at 16.8%, but it works in the opposite direction and reduces, rather than raises, risk.

3.9.3 Constructing longitudinal risk profiles

Following on from having established which predictors are significant and what the effect sizes are, the event history model can be used to predict the probability that a woman leaves work for the ten year period leading up to the state pension age of 60. This capacity to construct longitudinal trajectories leads to a more comprehensive understanding of how the factors associated with transition influence women’s employment chances as they age. Trajectories plotted in Figure 3.13 illustrate this point. In this figure the predicted conditional probability for each of the significant factors is plotted at each year of age between 51 and 59. In each case all other observed factors are held at either the median amount or reference category and the mean value is assumed for unobserved factors. The attributes associated with accelerated labour market exit - namely health, caring and partner’s employment status - are graphed in blue. Trajectories for renting or an outstanding mortgage are shown in red; these factors predict longer working lives.

The trajectory for a woman with poor self rated health is the highest in Figure 3.13 with pathways for women with caring responsibilities and with a retired partner or a deterioration in health status also high; this order reflects the ranking of significant predictors detailed in the previous section. This is the case throughout the studied age range - the predicted probabilities of transitioning that arise from having poor health, caring duties or a retired partner are similar and this holds irrespective of age. Likewise, the predictions that apply to women with a limiting health condition or to women with a non-working, non-retired partner are also similar to each other, as are those for women who rent or have an outstanding mortgage.
Figure 3.13: Significant predictor risk trajectories for women’s employment transitions

Note also that in Figure 3.13 the difference in magnitude of the predicted hazard for each listed attribute is minimal at younger ages, but becomes more pronounced as women approach state pension age. In younger years, the conditional probability of exit for is similar irrespective of health, caring, tenure or partner circumstances, but as women age differences arise between the identified groups of covariates. Those with poor self rated health, a retired partner or caring responsibilities develop higher risk profiles. This is consistent with these attributes having the largest estimated coefficients in the fitted model.

Figure 3.14 is an example of the more detailed risk profiles that can be constructed from the fitted event history models. Four different hypothetical trajectories are shown for the effect of self rated health status between the ages of 50 and 59. The top figure graphs two predicted trajectories; one for women with either consistently good health and the other for those with consistently poor health. For other typologies where health status could take either value at a given age, a woman will shift between these two paths. In times of poor self rated health the estimated hazard is given by the higher curve, and by the lower curve during periods of a good or better rating. The impact of having poor self rated health is a constant 74.4% and a woman’s predicted conditional probability of exit will increase by this amount in any year of age that she is recorded as having poor health.

The lower two panels of Figure 3.14 show predicted trajectories for women who experience one permanent change in health status. The pathway in Figure 3.14b depicts the
Figure 3.14: Predicted health trajectories for women’s employment transitions
expected outcome for a woman who has good health until the age of 53 and poor thereafter. At ages 51 and 52 this woman will have the same predicted probability of leaving work that other healthy women have; but, at the age of 53, her trajectory then follows that of women who rate their health as poor. Figure 3.14c illustrates hazard should the change in health occur at age 56. These figures illustrate the key methodological benefit of this research in that the impact of a given attribute on women’s employment can be measured and quantified, and at different points throughout the age range of interest; existing studies into women’s retirement are primarily qualitative in nature and do not provide this detail.

There is a caveat that applies to these health results. In the fitting of the event history model a woman’s record for a given year of age is treated independently from that at any other age. Consequently her health status at any particular age is analysed without reference to her health at any previous or subsequent time point. When the above hypothetical trajectories are interpreted, therefore, the estimated risk at any one age is the same irrespective of health history. In the lower two panels, the predicted conditional probability of leaving work at age 56, 57, 58 and 59 is the same even though in one the woman has three additional years of poor health status prior to age 56. This prior health history is not taken into account in the modelling process, but to do so would require an alternative analytic approach that can incorporate sequential dependent observations.

### 3.10 Summary

The first research question of this thesis was the subject of this chapter. Male partner’s ill health, spousal retirement status and household pension wealth were hypothesised predictors of older women’s labour market transitions that occur between the age of 50 and state pension age of 60. A series of discrete time event history models were constructed to consider evidence for this hypothesis. Results show that the timing of older women’s employment exit is influenced by the partner’s labour market position; those coupled to retired men have an estimated conditional probability of leaving work that is 57.8% higher than those with employed spouses. The increase in risk for women with partners in alternative non retired inactive states is an estimated 18.5%. No evidence was found for an effect of male partner health with women coupled to men with a limiting condition having the same predicted risk
of exit as those partnered to men without such a health problem. This result is explained with reference to two possible outcomes for an older woman in the advent of poor partner health; she may either leave work herself to provide care or alternatively remain in the workforce to ensure the economic well being of the family. The level of accumulated pension wealth in the household is also not a statistically significant predictor of older women’s labour market exit. We considered the effect of pension wealth quintile on the transition probability and find no association. Older women have the same level of estimated risk of labour force exit irrespective of their pension wealth quintile group.

In addition to the above results - that directly address the stated research question - the effect of women’s own health and caring responsibilities are established as significant for their labour market exit. The impact of these attributes is estimated at an increase of 74.4% for poor self rated health, 25.6% for limiting health conditions and 62.6% for a woman with caring duties. Women working part time hours are three times more likely to leave work than full time employees. Housing status is also influential with an outstanding mortgage associated with a reduction in risk of women’s transition by approximately 31.2%, and renting with a decrease of 16.8% compared to those who own outright. The results of this chapter show that the timing of older women’s exit from the labour market is dependent on the wider domestic context as well as own personal attributes, with partner’s employment particularly influential.
Chapter 4

Determinants of women’s voluntary and involuntary transitions

4.1 Introduction

The first research question of this thesis concerns the impact of household and partner characteristics on the occurrence and timing of older women’s employment transitions between the ages of 50 and the state pension age of 60. Specifically, partner’s health, partner’s employment status and household pension wealth were hypothesised predictors of early employment exit. In Chapter 3 these hypotheses were tested using a series of discrete time event history models fitted to sample data from the English Longitudinal Study of Ageing. No statistically significant evidence was found of a relationship between partner’s limiting health or the household pension wealth quintile and the incidence and timing of women’s exit from the labour force. Employment transitions do, however, depend on the labour market status of the male partner. Women partnered to retired men have a 57.8% higher risk of exit, whilst the risk differential for those coupled to men in other inactive states is 18.5%.

The aim of the earlier analysis was to determine the factors that influence the occurrence and timing of an exit out of work that occurs prior to state pension age. In this chapter we consider in more detail the nature of any transition that does occur. Women who have left work can enter a state of reported retirement, a caring role, unemployment or long term illness or disability. Movements into the latter three of these states are considered involuntary in that they are likely consequences of a negative event including health shocks or job loss.
Women who report as retired are classified as having a voluntary departure from the labour market that may have been influenced by the financial resources of the family. The second research question and hypotheses concern these factors that distinguish between voluntary and involuntary exit and are formally stated below.

**Research question 2** Does the impact of male partner characteristics and family financial resources vary across voluntary and involuntary pathways?

**Hypothesis 2a** Household pension wealth has a greater impact on women’s voluntary labour market exit into reported retirement prior to state pension age than on involuntary exit into alternative non-retired states.

**Hypothesis 2b** Involuntary transitions into non-retired states are influenced more by the health status of a woman or her partner than by household financial resources.

Addressing these research questions involves comparing the attributes of women from the ELSA sample who have an involuntary transition with those who enter retirement between the ages of 50 and 59. Results from this process will indicate which characteristics influence the odds of involuntary rather than voluntary exit, and quantify the impact that each has. In the next section sample statistics from the studied households are presented with an emphasis on the difference in transition rates of the two exit types. This difference in observed risk is considered for various subgroups of the sample as defined by women’s individual, household and partner attributes, including health and pension wealth as raised in the second research hypotheses above. This descriptive analysis will inform the subsequent modelling of transition type - this process is explained further in Section 4.3. Results of the fitted models are presented in Section 4.4, and the chapter concludes with a summary of findings in Section 4.5.

### 4.2 Descriptives of alternative exit groups

Two hundred and eighty seven women in the selected ELSA sample experienced a transition from employment. Addressing the second research question involves dividing these women
into two groups according to the destination state reported after leaving work. The first sub sample is comprised of those who describe their status as ‘retired’ following their transition. There are 134 women in this category and they are considered to have experienced voluntary transitions. The second sample consists of 153 women who report as either permanently sick or disabled, looking after home and family or unemployed; they are collectively regarded as having had ‘involuntary’ exits from work. The aim of this section is to consider how the transition rate into each destination state varies according to women’s different individual, household and domestic circumstances. Different groups of women defined by individual attributes including age and health are considered in Section 4.2.1; household measures of pension wealth, non pension wealth and tenure are discussed in Section 4.2.2 and male partner characteristics follow in Section 4.2.3. In each case, the value or status of a given attribute is taken as recorded in the respondent’s ELSA interview that immediately preceded their transition.

4.2.1 The effect of women’s individual characteristics

The focus of the analysis in Chapter 3 was the occurrence and timing of older women’s transitions out of work. The relationship between age and the probability of event occurrence was established first with women’s education, income, social class, health, caring responsibilities and working patterns considered after that. A similar structure is followed here, where we consider the type of transition that takes place. The observed rate of voluntary and involuntary exit for women of different ages is detailed first, in the next section.

4.2.1.1 Age

The final fitted model for predicting the timing of women’s transitions was based on a linear age hazard function, as shown in Model 2, Table 3.11 on page 145. The influence of age in this model is estimated at 0.362 on the cloglog scale, which converts to a 43.6% increase in the conditional probability of a woman leaving work for each additional year between the ages of 50 and 59. The objective now is to consider whether age also predicts the type of transition that occurs, in addition to the timing of it.

Figure 4.1a provides a visual representation of trajectories out of work for the sample of
287 transitioned women. The sequence index plot on the left shows the employment state for each of the women who entered a ‘not working, not retired’ state between the ages of 50 and 61. The right hand figure contains the same information for those who reported as retired. In each plot periods of employment are coded green, retirement in red and periods of caring, illness or unemployment in blue. Ages for which no status is available are shaded grey. This analysis is concerned with women’s first exit out of work after the age of 50, and if each graph is read from left to right, then a transition occurs with a change from green to either blue or red in the next period. If we compare the two index plots in Figure 4.1a
then it is apparent that a greater proportion of the involuntary transitions occur at younger ages with movements into retirement tending to happen later. The incidence of retirement is particularly marked at ages 56/57; in contrast, a higher percentage of women who leave into a non-retired state do so between the ages of 52 and 55. Women who transition into a caring role, unemployment or state of poor health therefore tend to have shorter working lives than their counterparts who report as retired.

The state distribution graphs in Figure 4.1b also show this difference between involuntary exit and voluntarily retired women. The left figure is constructed using data from respondents who report as having a caring role, being unemployed or permanently sick or disabled whereas the right figure is for those that report as retired prior to state pension age. A greater proportion of the early retired sample spent their early 50s in the workforce; between the ages of 52 and 55 over 80% of this group were employed compared to 60% of those who experienced an involuntary exit. At ages 56/57 approximately 70% of the voluntary exit group, but only 40% of the involuntary were still in work. At 58/59, however, there is less disparity with 40% of voluntary transitioned women in employment compared to just over 30% of the involuntary exit sample. These findings again suggest there is heterogeneity between women who enter a caring, unemployment or illness state and those who report as retired prior to 60.

Table 4.1: Number and percentage of women transitioned by type of exit and age

<table>
<thead>
<tr>
<th>Age</th>
<th>51</th>
<th>52</th>
<th>53</th>
<th>54</th>
<th>55</th>
<th>56</th>
<th>57</th>
<th>58</th>
<th>59</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary exit (n)</td>
<td>14</td>
<td>13</td>
<td>15</td>
<td>23</td>
<td>18</td>
<td>18</td>
<td>23</td>
<td>17</td>
<td>12</td>
</tr>
<tr>
<td>Percentage of exits involuntary</td>
<td>77.8</td>
<td>81.3</td>
<td>93.8</td>
<td>76.7</td>
<td>56.3</td>
<td>50.0</td>
<td>52.3</td>
<td>32.7</td>
<td>27.9</td>
</tr>
<tr>
<td>Voluntary early retirement (n)</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td>7</td>
<td>14</td>
<td>18</td>
<td>21</td>
<td>35</td>
<td>31</td>
</tr>
<tr>
<td>Percentage of exits voluntary</td>
<td>22.2</td>
<td>18.8</td>
<td>6.3</td>
<td>23.3</td>
<td>43.8</td>
<td>50.0</td>
<td>47.7</td>
<td>67.3</td>
<td>72.1</td>
</tr>
</tbody>
</table>

Figures in Table 4.1 show the frequency and percentage of women in the transitioned sample who entered each of the two destination states for every year in the studied age range. The proportion who report an involuntary exit declines over time, whereas the incidence of reported retirement is higher amongst older women. These observed transitioned rates are plotted in Figure 4.2 where the described trends are clearly seen; the distribution of involuntary transitions is skewed towards women of younger ages.
4.2.1.2 Education, income, social class and dependent children

The aim of the second research question in this thesis is to determine whether health and pension wealth have a differential impact on the incidence of involuntary and voluntary exit. To isolate the effects of health and wealth on transitions we first need to adjust for other characteristics and hence, in this section, the relationship between the type of transition that occurs and a woman’s income, education level, social class and dependent children is considered.

Figure 4.3 plots women’s individual income for each of the two transition types of interest. The top graph shows the income distribution for women who experience an involuntary transition and that for reported retired women is in the lower graph. The mean of each distribution is shown with a red dotted line. Women who leave the labour force involuntarily between the ages of 50 and 59 tend to have lower incomes than their retiring counterparts; the mean weekly incomes for these two groups are £158 and £264 respectively. Additionally, the incomes for the involuntary sample have a positive skew with the majority of women in this group earning less than the mean income of retired respondents. These findings indicate a negative relationship between income and the probability of transitioning into an involuntary state; those with lower incomes are more likely to exit into a caring role, unemployment or state of ill health than retirement prior to state pension age.
Observed transition rates according to a woman’s level of education, social class and the presence of dependent children are given in Table 4.2. There is a clear association between education and the type of event observed; 61.2% of women with a low level of education and 62.8% of those educated to O-level equivalent experience an involuntary transition compared to 35.8% of the most highly educated respondents. A similar relationship is seen across different social class strata. Involuntary exits are approximately twice as likely to occur for women from either routine/manual or intermediate groups than they are for women with a managerial or professional classification. Specifically, 65.3% of women from a routine/manual class and 63.0% with an intermediate designation entered a caring, unemployed or illness state compared to only 32.0% of managerial or professional level respondents.

The final factor considered here is the presence of dependent children aged 17 or under. A higher proportion of women with resident children experience an involuntary transition compared to those without children; 58.3% of women with children residing at home report as either caring, illness or unemployment compared to 52.3% of women without a resident child.

4.2.1.3 Health, caring and working patterns

In this section descriptive measures relating to the type of transition that occurs and women’s health, caring and working hours are presented. These are the individual level factors that
Table 4.2: Distribution of women’s voluntary and involuntary transitions for individual level socio demographic variables

<table>
<thead>
<tr>
<th>Education</th>
<th>Social class</th>
<th>Dependent child</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lower than O level</td>
<td>O level</td>
</tr>
<tr>
<td>Involuntary exit (n)</td>
<td>60</td>
<td>59</td>
</tr>
<tr>
<td>Involuntary transition rate (%)</td>
<td>61.2</td>
<td>62.8</td>
</tr>
<tr>
<td>Voluntary exit (n)</td>
<td>38</td>
<td>35</td>
</tr>
<tr>
<td>Voluntary transition rate (%)</td>
<td>38.8</td>
<td>37.2</td>
</tr>
</tbody>
</table>

Table 4.3: Distribution of voluntary and involuntary women’s transitions for key individual level covariates

<table>
<thead>
<tr>
<th>Caring duties</th>
<th>Limiting health</th>
<th>Poor self rated</th>
<th>Part time hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Involuntary exit (n)</td>
<td>115</td>
<td>38</td>
<td>123</td>
</tr>
<tr>
<td>Involuntary transition rate (%)</td>
<td>53.7</td>
<td>52.1</td>
<td>55.4</td>
</tr>
<tr>
<td>Voluntary exit (n)</td>
<td>99</td>
<td>35</td>
<td>99</td>
</tr>
<tr>
<td>Voluntary transition rate (%)</td>
<td>46.3</td>
<td>47.9</td>
<td>44.6</td>
</tr>
</tbody>
</table>
are of primary interest in this thesis and it was concluded from the analysis of Chapter 3 that having a limiting health condition, poor self rated health or a decline in health raises the risk of exit from employment prior to state pension age. Women with caring responsibilities and part time workers were also found to have a higher probability of leaving work. Of interest here is whether these attributes might also determine whether the transition that takes place is voluntary or involuntary in nature. The indicator for decline in health status has too few observations in each of the voluntary and involuntary transition categories to provide a reliable estimate and is therefore not considered at this stage.

Table 4.3 contains observed involuntary and voluntary transition rates for subgroups of transitioned women that are defined by their caring duties, health status and working hours. Just over half (52.1%) of women who had provided care, whilst they were still working experienced an involuntary transition with the remaining 47.9% of carers reporting early retirement. These rates are similar to those observed in the non-carer population; 53.7% of this group had an involuntary exit with 46.3% voluntary transitions. This indicates that caring may not be associated with a higher incidence of involuntary exit; this will be formally tested in the later modelling process.

There is evidence from the observed transition rates given in Table 4.3 of a possible relationship between poor self rated health and involuntary exit. Sixty percent of women with poor self reported health experienced this type of transition, whereas the incidence of involuntary exit amongst respondents with good self rated health is lower, at 52.2%. A limiting health condition, however, is associated with an apparent reduced risk of involuntary exit; 46.1% of women with a limiting condition had this type of transition compared to 55.4% of women with no such health problem.

The difference in voluntary and involuntary transition rates between the two health measures reflects a greater tendency for women with limiting conditions to report as retired. Fifty three percent of transitioned respondents with limiting health reported as retired, 12.3% as permanently sick or disabled and 29.2% in a caring role. Among those with poor self rated health, only 40% identified as retired after their transition, but 25% reported as permanently sick or disabled and 35% as caring for home or family. Women with poor self rated health, therefore, are more likely than those with limiting health to report one of the sick or disabled
or caring states that define an involuntary transition.

The probability of an involuntary exit is higher for women who work part time than it is for full time employees. In this sample 59.8% of part time workers entered a caring, unemployment or ill health state after they left work - this is notably higher than the 39.8% of full time employees who did so.

4.2.2 Sample transition rates according to household characteristics

Observed transition rates according to household characteristics are presented in this section. The two wealth measures - of accrued pension and non pension wealth - are considered first, followed by women’s housing status.

4.2.2.1 Pension and non pension wealth

The first research question asks whether older women’s exit from the labour force is related to the level of financial resources in the household, but in the event history models presented in Chapter 3 neither wealth indicator was statistically significant. Both wealth measures are structured into quintile groups with the most affluent forming the reference category; the earlier results indicate that the timing and occurrence of employment exit for women in each of the four lower quintiles is not significantly different from that of women in the wealthiest fifth of households. This holds for both pension and non-pension resources.

The second research question asks if financial resources determine the nature of labour market exit, with a hypothesis that household pension wealth has a greater influence on women’s voluntary reported retirement prior to state pension age than on involuntary withdrawal. If this were the case, we would expect women from the highest quintile groups to have lower involuntary transition rates. Table 4.4 contains the observed sample transition rates for each pension wealth and non-pension wealth quintile group. Considering pension wealth first, and there is an apparent negative relationship between the quintile group and the proportion of women who experienced an involuntary transition; 74.6% of the poorest women had this type of event compared to 48.9% of respondents from the middle quintile and 26.5% of those from the wealthiest. The incidence of reported retirement is higher amongst wealthier women, with 73.5% of those in the highest quintile group having a vol-
Table 4.4: Voluntary and involuntary women’s employment transitions by household level wealth measures

<table>
<thead>
<tr>
<th></th>
<th>Pension wealth quintile</th>
<th>Non pension wealth quintile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poorest</td>
<td>2</td>
</tr>
<tr>
<td>Involuntary exit (n)</td>
<td>50</td>
<td>37</td>
</tr>
<tr>
<td>Involuntary transition rate (%)</td>
<td>74.6</td>
<td>69.8</td>
</tr>
<tr>
<td>Voluntary exit (n)</td>
<td>17</td>
<td>16</td>
</tr>
<tr>
<td>Voluntary transition rate (%)</td>
<td>25.4</td>
<td>30.2</td>
</tr>
</tbody>
</table>
Table 4.5: Distribution of voluntary and involuntary women’s employment transitions according to tenure

<table>
<thead>
<tr>
<th></th>
<th>Own outright</th>
<th>Mortgage</th>
<th>Rent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary exit (n)</td>
<td>62</td>
<td>78</td>
<td>13</td>
</tr>
<tr>
<td>Involuntary transition rate (%)</td>
<td>52.1</td>
<td>52.7</td>
<td>65.0</td>
</tr>
<tr>
<td>Voluntary exit (n)</td>
<td>57</td>
<td>70</td>
<td>7</td>
</tr>
<tr>
<td>Voluntary transition rate (%)</td>
<td>47.9</td>
<td>47.3</td>
<td>35.0</td>
</tr>
</tbody>
</table>

Voluntary exit. These figures suggest that women with lower levels of accrued pension wealth, who leave work prior to state pension age, are more likely to report as having a caring role, as unemployed or with poor health whereas their wealthier counterparts tend to report as retired.

The relationship between observed rates of involuntary transition and non pension resources is not as distinct as that for pension wealth. Figures in Table 4.4 show that women from the two poorest quintile groups have the highest incidence of involuntary exit with 63.8% of the lowest group and 68.0% of the second quintile having this type of transition. However involuntary transition rates do not consistently decline for women in the middle and wealthier groups with observed exit percentages for the third, fourth and highest quintiles of 40.4%, 58.7% and 41.4% respectively. The next stage in the analysis, which follows this exploratory work, will formally compare the rate of involuntary exit from each of the four lower quintile groups with that of the wealthiest.

4.2.2.2 Tenure

Women in this ELSA sample are categorized according to one of three housing states. The first is comprised of women residing in homes that are owned outright. This group forms the reference category against which others are compared; women in properties with outstanding mortgages and those in rental properties form the alternative comparison groups.

The incidence of involuntary transition for each tenure group is shown in Table 4.5. A similar proportion of involuntary exit is seen within women from mortgaged residences and homes owned outright, with observed rates of 52.7% and 52.1% respectively. The rate of involuntary exit is, however, notably higher for women in rental properties. Sixty five percent of this group reported a caring, ill or unemployed state after they left work with only
35% reporting as retired, although this is based on a relatively small sample of twenty cases.

### 4.2.3 Observed transition type according to partner characteristics

The second hypothesis of this thesis states that experiencing an involuntary transition prior to state pension age is influenced more by the health status of a woman or her partner than by financial resources. Wealth was considered in the previous section; here we present sample statistics relating to partner’s health with their employment status also considered. Prior to this the age and income distributions of the male spouses are summarised.

#### 4.2.3.1 Male partner age and income distributions

![Figure 4.4: Distribution of male partner’s age by transition type](image)

Women between the ages of 50 and 59 are selected for this research, but there is no restriction on the age of the male member of the chosen households. The sample of 1569 couples analysed in Chapter 3 included male partners ranging in age from 31 to 87 years, with a median of 57; in the sample of 287 households with transitioned women, male spousal ages range from 39 to 87 with median 59 years. Figure 4.4 shows the distribution of partner ages for the transitioned subset according to the type of exit that occurred. The upper plot shows the ages of men partnered to women who have experienced an involuntary exit, whilst the lower is for men partnered to women who report as retired prior to state pension age.
The dashed line indicates the mean age for each group. The partners of women who had an involuntary transition have a mean age of 58 years, whilst men coupled to retired women have a slightly higher mean age of 60.

The distribution of male spouses’ weekly income for each transition type is shown in Figure 4.5. The two groups show a similar range of incomes, although the partners of women who reported as retired have a median income of £346 compared to £300 for spouses of women who experienced involuntary exit.

![Figure 4.5: Distribution of male partner’s income by type of transition](image)

### 4.2.3.2 Male partner health and employment status

The health measure used here indicates the presence of a limiting condition amongst the male partners in the sampled households. Table 4.6 shows the proportion of transitioned women with each type of exit according to the health status of the partner. Of the sample of women who left work, and who had a partner with a limiting condition, 55.6% experienced an involuntary exit with the remaining 44.4% reporting as retired; in comparison, the involuntary transition rate for women partnered to healthy men was slightly lower at 52.4% with a retirement rate of 47.6%. Whether these sample statistics provide sufficient evidence to conclude that partner health does determine the type of exit women experience is addressed later in the modelling process.

We also consider here the impact that male partner’s employment status might have on
### Table 4.6: Voluntary and involuntary women's transitions by male partner's health and employment status

<table>
<thead>
<tr>
<th></th>
<th>Health of male partner</th>
<th>Employment of male partner</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No limiting condition</td>
<td>Limiting condition</td>
</tr>
<tr>
<td>Involuntary exit (n)</td>
<td>108</td>
<td>45</td>
</tr>
<tr>
<td>Involuntary transition rate (%)</td>
<td>52.4</td>
<td>55.6</td>
</tr>
<tr>
<td>Voluntary exit (n)</td>
<td>98</td>
<td>36</td>
</tr>
<tr>
<td>Voluntary transition rate (%)</td>
<td>47.6</td>
<td>44.4</td>
</tr>
</tbody>
</table>
determining the type of women’s transition that occurs. The men of the studied households
are categorized into one of three groups: employed, retired, or an amalgamation of unem-
ployed, permanently sick or disabled and looking after home and family. This third group is
also referred to as containing ‘not working, not retired’ men. These categories are analogous
to those used for women’s destination states. Table 4.6 shows the percentage of women that
experience either an involuntary or voluntary transition according to the labour market posi-
tion of the male spouse. The highest incidence of involuntary exit is observed amongst those
partnered to men who are neither working nor retired, with 70% of women also reporting this
status after leaving work. Women coupled to retired men, in contrast, had a notably lower
involuntary transition rate of 24.1%. The rate of observed involuntary exit for those with
working partners was 58.7%. These figures suggest that the odds of an older woman having
an involuntary transition might differ according to the labour market status of her spouse or
partner.

4.3 Method

The analysis presented in this chapter relates to the second research question of the the-
sis, and concerns the factors that influence the likelihood of older women’s voluntary and
involuntary labour market transitions. The methodological approach relevant to this stage
of the analysis was fully explained in Section 2.3.2 of Chapter 2; to briefly summarise, a
logistic regression model is fitted to the sample of transitioned women’s data. This model
is reproduced below as Equation 4.1. The outcome measure is the log odds of individual $i$
experiencing an involuntary transition relative to voluntary exit. Estimated parameters are
contained in the vector $\beta$ with covariates in $x_i$, and the model is estimated in stages with indi-
vidual level measures incorporated first, followed by household and then partner indicators.
Results of this process are detailed in the next section.

\[
\text{logit}\left(\frac{p_i}{1 - p_i}\right) = \alpha + \beta^T x_i
\]  
(4.1)
4.4 Results

Here the results from the fitted model specified in Equation 4.1 are presented. The first set of models incorporate age and the control factors of income, education, social class and the presence of dependent children. Results for these are given in Section 4.4.1. Following that estimates for the main individual level predictors of interest - health, caring and working hours - are in Section 4.4.2 and results for the household and partner attributes are in Sections 4.4.3 and 4.4.4 respectively.

4.4.1 Age and control factors

Descriptive statistics summarised in Section 4.2.1 showed that women’s involuntary employment exit tends to occur at younger ages, with reported retirement prior to state pension age more prevalent amongst older women. The first logistic regression model constructed contains a linear term for age, and has an estimated coefficient of -0.3618. This is statistically significant ($\chi^2(1) = 0.4360, p < 0.001$), and as such supports the earlier evidence of a negative relationship between age and the probability of an involuntary exit. A quadratic term was tested, but this did not further improve the model fit ($\chi^2(1) = 0.4753, p = 0.49$); the linear term sufficiently captures the age effect. When exponentiated the coefficient of -0.3618 on the logit scale corresponds to odds of 0.6964. For each additional year of age between 50 and 59 that is spent in employment, an older woman’s odds of involuntary transition rather than voluntary retirement decreases by a factor of approximately 70%.

Measures of income, education and social class and an indicator for the presence of children are added to the model containing the linear age effect. Results are given in Model 1, Table 4.7 on page 173. As a group these four covariates improve the fit of the model ($\chi^2(6) = 32.82, p < 0.001$); however the primary reason for including these indicators is to isolate the effects of the health and caring variables that are entered next, and consequently results are only briefly summarised here.

Earlier exploratory analysis suggested a negative relationship between income and the probability of involuntary exit and results of Model 1 support this. The coefficient for income is estimated at -0.404 on the logit scale; the lower a woman’s income, therefore, the more
likely she is to experience an involuntary exit rather than report as retired. Results for the education variable show that the odds of involuntary exit are not significantly influenced by a woman’s level of education, but social class does have an impact, with women from the intermediate group approximately \( e^{0.907} = 2.5 \) times more likely to experience an involuntary exit than those from the managerial or professional class. The effect being in a routine or manual class is similar with odds of involuntary transition for these women an estimated \( e^{0.967} = 2.6 \) times higher than for those from a managerial or professional group.

The final control variable adjusts for the presence of children. The observed involuntary transition rate for women with resident children was 58.3% compared to 52.3% for those without children present. In Model 1 the estimated coefficient for this measure suggests that this difference is not statistically significant, and having resident children does not alter the odds that a woman experiences an involuntary rather than voluntary exit.

### 4.4.2 Key individual factors: health, caring and working hours

The main individual level attributes of interest in this research are women’s health, caring responsibilities and working hours. Indicators for each of these variables are incorporated into the model and the resulting estimated coefficients and confidence intervals are in Table 4.7, Models 2 - 5. Women with limiting health conditions are as likely to experience an involuntary transition as they are to report as retired prior to state pension age (\( \chi^2(1) = 0.4013, p = 0.5264 \)); this conclusion also holds for women with poor self rated health (\( \chi^2(1) = 0.1713, p = 0.6789 \)). Having caring responsibilities also does not predict involuntary exit with voluntary early retirement as probable (\( \chi^2(1) = 0.4948, p = 0.4818 \)). The type of transition that occurs is also independent of working patterns with part time employees having the same odds of involuntary transition as full time workers (\( \chi^2(1) = 0.0354, p = 0.8507 \)).

### 4.4.3 Household factors: wealth and tenure

The three household level factors considered in this research are pension wealth, non pension wealth and housing status. Results from incorporating these variables are given in Table 4.8, Model 1 and show that pension wealth is a statistically significant predictor of the type of
Table 4.7: Parameter estimates from logistic regression model for women’s involuntary transition from employment, with individual level covariates

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Limiting health</th>
<th>Self rated health</th>
<th>Caring</th>
<th>Part time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.333***</td>
<td>-0.330***</td>
<td>-0.334***</td>
<td>-0.331***</td>
<td>-0.333***</td>
</tr>
<tr>
<td></td>
<td>(-0.460,-0.206)</td>
<td>(-0.457,-0.203)</td>
<td>(-0.461,-0.207)</td>
<td>(-0.458,-0.204)</td>
<td>(-0.460,-0.206)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>0.204</td>
<td>0.190</td>
<td>0.210</td>
<td>0.234</td>
<td>0.206</td>
</tr>
<tr>
<td></td>
<td>(-0.474,0.882)</td>
<td>(-0.489,0.870)</td>
<td>(-0.468,0.889)</td>
<td>(-0.450,0.917)</td>
<td>(-0.473,0.884)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>-0.037</td>
<td>-0.045</td>
<td>-0.026</td>
<td>-0.026</td>
<td>-0.033</td>
</tr>
<tr>
<td></td>
<td>(-0.820,0.745)</td>
<td>(-0.829,0.740)</td>
<td>(-0.810,0.757)</td>
<td>(-0.811,0.760)</td>
<td>(-0.816,0.751)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.907**</td>
<td>0.900**</td>
<td>0.906**</td>
<td>0.903**</td>
<td>0.899**</td>
</tr>
<tr>
<td></td>
<td>(0.141,1.673)</td>
<td>(0.132,1.668)</td>
<td>(0.141,1.672)</td>
<td>(0.137,1.670)</td>
<td>(0.128,1.670)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>0.967**</td>
<td>0.980**</td>
<td>0.952**</td>
<td>0.994**</td>
<td>0.957**</td>
</tr>
<tr>
<td></td>
<td>(0.176,1.758)</td>
<td>(0.187,1.773)</td>
<td>(0.159,1.746)</td>
<td>(0.197,1.790)</td>
<td>(0.159,1.754)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>0.006</td>
<td>-0.005</td>
<td>0.010</td>
<td>-0.005</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td>(-0.722,0.734)</td>
<td>(-0.734,0.724)</td>
<td>(-0.719,0.739)</td>
<td>(-0.734,0.725)</td>
<td>(-0.731,0.731)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.404**</td>
<td>-0.400**</td>
<td>-0.407**</td>
<td>-0.412**</td>
<td>-0.393**</td>
</tr>
<tr>
<td></td>
<td>(-0.720,-0.088)</td>
<td>(-0.714,-0.086)</td>
<td>(-0.726,-0.088)</td>
<td>(-0.731,-0.093)</td>
<td>(-0.727,-0.059)</td>
</tr>
<tr>
<td>Limiting health condition (ref:no)</td>
<td>-0.203</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.832,0.426)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.166</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-0.620,0.952)</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.223</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-0.844,0.398)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-0.583,0.707)</td>
</tr>
<tr>
<td>Constant</td>
<td>3.483***</td>
<td>3.501***</td>
<td>3.480***</td>
<td>3.547***</td>
<td>3.391***</td>
</tr>
<tr>
<td></td>
<td>(1.540,5.426)</td>
<td>(1.565,5.437)</td>
<td>(1.524,5.436)</td>
<td>(1.585,5.510)</td>
<td>(1.242,5.540)</td>
</tr>
<tr>
<td>Observations</td>
<td>287</td>
<td>287</td>
<td>287</td>
<td>287</td>
<td>287</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-160.093</td>
<td>-159.893</td>
<td>-160.008</td>
<td>-159.846</td>
<td>-160.076</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>336.187</td>
<td>337.785</td>
<td>338.005</td>
<td>337.692</td>
<td>338.151</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
transition that occurs ($\chi^2(4) = 16.122, p = 0.0029$). The reference category for this variable is the wealthiest quintile, and the exponentiated coefficients give the odds of an involuntary exit relative to this group. The estimated coefficients are consistently positive and decrease in magnitude; this shows that women in the wealthiest households are least likely to have an involuntary exit, whilst the poorest women are at highest risk. Those from the poorest pension group have estimated odds of involuntary exit that are $e^{1.770} = 5.87$ times higher than for women in the wealthiest group, with the odds ratio for women in the second poorest group $e^{1.436} = 4.20$ times greater.

This analysis also allows us to estimate the odds of involuntary exit for women in the middle wealth groups who, as was highlighted in the literature review of Chapter 1, are currently under-researched as studies tend to focus on those at the extremes of the wealth distribution. Those in the middle and second highest quintile groups have significantly different odds of involuntary transition compared to the wealthiest; in both the third and fourth quintiles women have odds of involuntary transition that are more than twice as high as their wealthier counterparts. Specifically, the estimated odds ratio for women in the second highest group is $e^{0.802} = 2.2$ times greater and for the middle group, this ratio is $e^{0.928} = 2.5$ times higher.

The level of non-pension wealth that a couple has accrued also determines the type of exit an older women is likely to experience ($\chi^2(4) = 13.573, p = 0.0088$). Estimated coefficients for this variable - given in Table 4.8, Model 2 - are all positive. This indicates that the odds of involuntary rather than voluntary exit is lowest for women in the wealthiest twenty percent of couples. There is, however, evidence of a non-linear relationship between non-pension wealth and transition type. Women from the least affluent households are $e^{1.159} = 3.2$ times as likely as the most affluent to exit involuntarily, but the odds for the second poorest and middle groups are $e^{1.466} = 4.3$ and $e^{0.248} = 1.3$ respectively. The estimated odds for women in the second wealthiest quintile is $e^{1.065} = 2.9$. These estimates are high, but with relatively wide confidence intervals are commensurate with findings from descriptive analysis given earlier in Section 4.2.2.

Results in Table 4.8, Model 3 are those for the model incorporating the tenure covariate. The tenure variable in this model is not statistically significant ($\chi^2(2) = 0.8601, p = 0.6505$),
Table 4.8: Parameter estimates from logistic regression model for women’s involuntary transition from employment, with household level covariates

<table>
<thead>
<tr>
<th></th>
<th>Pension wealth (1)</th>
<th>Non pension wealth (2)</th>
<th>Tenure (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td>-0.340***</td>
<td>-0.375***</td>
<td>-0.338***</td>
</tr>
<tr>
<td></td>
<td>(-0.473,-0.206)</td>
<td>(-0.511,-0.239)</td>
<td>(-0.469,-0.208)</td>
</tr>
<tr>
<td><strong>Education (ref: less than O level)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>0.427</td>
<td>0.342</td>
<td>0.208</td>
</tr>
<tr>
<td></td>
<td>(-0.297,1.151)</td>
<td>(-0.379,1.064)</td>
<td>(-0.486,0.903)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>0.325</td>
<td>0.294</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(-0.520,1.171)</td>
<td>(-0.552,1.139)</td>
<td>(-0.794,0.800)</td>
</tr>
<tr>
<td><strong>Social class (ref: managerial/professional)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.728*</td>
<td>0.925**</td>
<td>0.890**</td>
</tr>
<tr>
<td></td>
<td>(-0.070,1.526)</td>
<td>(0.127,1.724)</td>
<td>(0.114,1.666)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>0.669</td>
<td>0.781*</td>
<td>0.959**</td>
</tr>
<tr>
<td><strong>Dependent child (ref: no)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.178,1.517)</td>
<td>(-0.061,1.623)</td>
<td>(0.150,1.768)</td>
</tr>
<tr>
<td></td>
<td>-0.126</td>
<td>-0.017</td>
<td>-0.074</td>
</tr>
<tr>
<td></td>
<td>(-0.890,0.637)</td>
<td>(-0.767,0.734)</td>
<td>(-0.822,0.675)</td>
</tr>
<tr>
<td><strong>Individual income (log)</strong></td>
<td>-0.317**</td>
<td>-0.358**</td>
<td>-0.407**</td>
</tr>
<tr>
<td></td>
<td>(-0.632,-0.002)</td>
<td>(-0.669,-0.047)</td>
<td>(-0.751,-0.063)</td>
</tr>
<tr>
<td><strong>Limiting health condition (ref: no)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.939,0.449</td>
<td>-0.888,0.503</td>
<td>(0.959,0.391)</td>
</tr>
<tr>
<td><strong>Poor self rated health (ref: good or better)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.149</td>
<td>0.126</td>
<td>0.251</td>
</tr>
<tr>
<td></td>
<td>(-0.727,1.026)</td>
<td>(-0.758,1.010)</td>
<td>(-0.601,1.102)</td>
</tr>
<tr>
<td><strong>Recently provided care (ref: no)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.233</td>
<td>-0.477</td>
<td>-0.211</td>
</tr>
<tr>
<td></td>
<td>(-0.880,0.414)</td>
<td>(-1.139,0.184)</td>
<td>(-0.838,0.415)</td>
</tr>
<tr>
<td><strong>Part time (ref: full time)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.087</td>
<td>0.246</td>
<td>0.068</td>
</tr>
<tr>
<td></td>
<td>(-0.584,0.759)</td>
<td>(-0.424,0.915)</td>
<td>(-0.587,0.723)</td>
</tr>
<tr>
<td><strong>Household pension wealth (ref: wealthiest)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>1.770***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.832,2.708)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>1.436***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.496,2.376)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle quintile</td>
<td>0.928*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.007,1.863)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>0.802*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.057,1.661)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Household non pension wealth (ref: wealthiest)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td></td>
<td></td>
<td>1.159**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.143,2.175)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td></td>
<td></td>
<td>1.466***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.494,2.438)</td>
</tr>
<tr>
<td>Middle quintile</td>
<td></td>
<td></td>
<td>0.248</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-0.623,1.119)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td></td>
<td></td>
<td>1.065**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.211,1.919)</td>
</tr>
<tr>
<td><strong>Tenure (ref: owns home outright)</strong></td>
<td></td>
<td></td>
<td>0.228</td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td></td>
<td></td>
<td>(-0.343,0.798)</td>
</tr>
<tr>
<td>Rents</td>
<td></td>
<td></td>
<td>0.420</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-0.780,1.619)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>2.152*</td>
<td>2.678**</td>
<td>3.445***</td>
</tr>
<tr>
<td></td>
<td>(-0.020,4.324)</td>
<td>(0.575,4.781)</td>
<td>(1.220,5.670)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>287</td>
<td>287</td>
<td>287</td>
</tr>
<tr>
<td><strong>Log Likelihood</strong></td>
<td>-151.376</td>
<td>-152.650</td>
<td>-159.007</td>
</tr>
<tr>
<td><strong>Akaike Inf. Crit.</strong></td>
<td>334.751</td>
<td>337.300</td>
<td>346.013</td>
</tr>
</tbody>
</table>

*Note:* ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01
meaning there is insufficient evidence to conclude that tenure is associated with the type of labour market exit that occurs. The reference category for this variable is homes owned outright, and results therefore show that there is no significant difference in the odds of involuntary exit for renters or mortgagees compared to women residing in homes owned outright.

4.4.4 Partner factors

Measures of male partner attributes are introduced in two stages, with control measures of age and income entered first and health and employment indicators following that. Estimated coefficients and confidence intervals for these models are in Table 4.9 on page 177 and are described in the next two sections.

4.4.4.1 Control factors: age, income

Partner’s age and income enter the model simultaneously and both as continuous measures. Results are given in Table 4.9, Model 1. These measures are not statistically significant ($\chi^2(2) = 2.1196, p = 0.3465$) and suggest that the odds of an older woman experiencing an involuntary employment transition are independent from her partner’s age and income.

4.4.4.2 Key factors: health, employment status

Male partner health is of primary interest in the second research question of this thesis. The relevant hypothesis states that involuntary transitions are influenced more by the health status of a woman or her partner than by household financial resources. Results from incorporating the indicator for male spousal health are given in Table 4.9, Model 2. There is no evidence to suggest partner’s health is a significant predictor of involuntary exit ($\chi^2(1) = 0.5866, p = 0.4437$); having a partner with a limiting health condition does not increase the odds of an older woman having an involuntary, rather than voluntary, transition from work.

The covariate for male partner’s employment compares the probability of an involuntary transition for women with retired spouses, and with spouses in alternative non working states, to that of women coupled to working men. The alternative non working states incorporate the unemployed, long term ill and those looking after home and family. Results for this
Table 4.9: Parameter estimates from logistic regression model for women’s involuntary transition from employment, with male partner level covariates

<table>
<thead>
<tr>
<th></th>
<th>Partner control (1)</th>
<th>Partner limiting health (2)</th>
<th>Partner’s employment (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>-0.344***</td>
<td>-0.342***</td>
<td>-0.341***</td>
</tr>
<tr>
<td></td>
<td>(-0.498,-0.190)</td>
<td>(-0.496,-0.187)</td>
<td>(-0.501,-0.182)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td>0.830</td>
<td>0.854</td>
<td>0.673</td>
</tr>
<tr>
<td>O level equivalent</td>
<td>0.587</td>
<td>0.590</td>
<td>0.633</td>
</tr>
<tr>
<td></td>
<td>(-0.186,1.359)</td>
<td>(-0.183,1.363)</td>
<td>(-0.168,1.435)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>0.622</td>
<td>0.621</td>
<td>0.569</td>
</tr>
<tr>
<td></td>
<td>(-0.287,1.531)</td>
<td>(-0.288,1.530)</td>
<td>(-0.360,1.498)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.830*</td>
<td>(-0.021,1.681)</td>
<td>(-0.197,1.544)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>0.598</td>
<td>0.616</td>
<td>0.514</td>
</tr>
<tr>
<td></td>
<td>(-0.303,1.498)</td>
<td>(-0.286,1.518)</td>
<td>(-0.410,1.437)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.242</td>
<td>-0.265</td>
<td>-0.292</td>
</tr>
<tr>
<td></td>
<td>(-1.057,0.573)</td>
<td>(-1.081,0.552)</td>
<td>(-1.121,0.537)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.319**</td>
<td>-0.327**</td>
<td>-0.364**</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>-0.188</td>
<td>-0.197</td>
<td>-0.209</td>
</tr>
<tr>
<td></td>
<td>(-0.637,-0.002)</td>
<td>(-0.650,-0.005)</td>
<td>(-0.727,-0.0003)</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>-0.923,0.547</td>
<td>-0.931,0.537</td>
<td>-0.964,0.547</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>-1.181,0.222</td>
<td>-1.208,0.200</td>
<td>-1.331,0.175</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>0.193</td>
<td>0.202</td>
<td>0.187</td>
</tr>
<tr>
<td></td>
<td>(-0.509,0.895)</td>
<td>(-0.503,0.908)</td>
<td>(-0.537,0.911)</td>
</tr>
<tr>
<td>Household pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>1.756***</td>
<td>1.734***</td>
<td>1.729***</td>
</tr>
<tr>
<td></td>
<td>(0.733,2.780)</td>
<td>(0.706,2.761)</td>
<td>(0.672,2.786)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>1.270**</td>
<td>1.258**</td>
<td>1.229**</td>
</tr>
<tr>
<td></td>
<td>(0.257,2.284)</td>
<td>(0.241,2.274)</td>
<td>(0.199,2.258)</td>
</tr>
<tr>
<td>Middle quintile</td>
<td>0.749</td>
<td>0.715</td>
<td>0.692</td>
</tr>
<tr>
<td></td>
<td>(-0.240,1.738)</td>
<td>(-0.279,1.709)</td>
<td>(-0.312,1.696)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>0.683</td>
<td>0.639</td>
<td>0.767</td>
</tr>
<tr>
<td></td>
<td>(-0.234,1.600)</td>
<td>(-0.288,1.566)</td>
<td>(-0.182,1.715)</td>
</tr>
<tr>
<td>Household non pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>0.842</td>
<td>0.773</td>
<td>0.564</td>
</tr>
<tr>
<td></td>
<td>(-0.336,2.019)</td>
<td>(-0.417,1.962)</td>
<td>(-0.657,1.784)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>1.282**</td>
<td>1.276**</td>
<td>1.039**</td>
</tr>
<tr>
<td></td>
<td>(0.232,2.331)</td>
<td>(0.225,2.327)</td>
<td>(-0.049,2.127)</td>
</tr>
<tr>
<td>Middle quintile</td>
<td>-0.024</td>
<td>-0.025</td>
<td>-0.164</td>
</tr>
<tr>
<td></td>
<td>(-0.952,0.905)</td>
<td>(-0.956,0.906)</td>
<td>(-1.118,0.791)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>1.108**</td>
<td>1.135**</td>
<td>1.027**</td>
</tr>
<tr>
<td></td>
<td>(0.192,2.025)</td>
<td>(0.212,2.059)</td>
<td>(0.088,1.966)</td>
</tr>
<tr>
<td>Tenure (ref: owns home outright)</td>
<td>0.042</td>
<td>0.036</td>
<td>-0.110</td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>-0.092</td>
<td>-0.142</td>
<td>-0.261</td>
</tr>
<tr>
<td></td>
<td>(-1.495,1.311)</td>
<td>(-1.549,1.265)</td>
<td>(-1.736,1.214)</td>
</tr>
<tr>
<td>Male partner age</td>
<td>-0.047</td>
<td>-0.051</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(-0.116,0.022)</td>
<td>(-0.122,0.020)</td>
<td>(-0.103,0.051)</td>
</tr>
<tr>
<td>Male partner income (log)</td>
<td>-0.035</td>
<td>-0.035</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(-0.188,0.118)</td>
<td>(-0.189,0.119)</td>
<td>(-0.210,0.122)</td>
</tr>
<tr>
<td>Male partner limiting health condition (ref:no)</td>
<td>0.267</td>
<td>0.220</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.418,0.953)</td>
<td>(-0.535,0.974)</td>
<td></td>
</tr>
<tr>
<td>Male partner’s employment status (ref: employed)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>-1.143**</td>
<td>-2.061,-0.225</td>
<td>0.558</td>
</tr>
<tr>
<td></td>
<td>(-2.061,-0.225)</td>
<td>(-0.683,1.799)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>4.477*</td>
<td>4.691*</td>
<td>3.937</td>
</tr>
<tr>
<td></td>
<td>(-0.242,9.197)</td>
<td>(-0.109,9.492)</td>
<td>(-1.156,9.030)</td>
</tr>
</tbody>
</table>

Observations 287 287 287  
Log Likelihood -144.136 -143.843 -139.121  

Note: *p<0.1; **p<0.05; ***p<0.01
variable are in Table 4.9, Model 3 and show that partner’s employment status is statistically significant ($\chi^2(2) = 9.4433, p = 0.0089$). If her spouse is either in a caring role, unemployed or long term sick or disabled, then a woman who has left work is $e^{0.558} = 1.8$ times more likely to exit involuntarily and also enter one of these labour states. Women with a retired partner have reduced odds of an involuntary transition, by a factor of $e^{-1.143} = 0.3$. These women are more likely to report as retired after they transition. These findings suggest that there is a tendency for older women who leave work prior to state pension age to enter the same labour market position as their spouse.

4.5 Summary

The aim of this thesis is to establish the relationship between older women’s transitions out of work and the wider domestic context in which their employment trajectories unfold. Our analysis concentrates on coupled women aged between 50 and state pension age, and of particular interest are the impact of the male partner’s health, partner employment status and household pension wealth on employment pathways. The first research question asks whether these attributes influence the occurrence and timing of women’s labour market exit. This question was addressed in Chapter 3 where a series of event history models were fitted to ELSA data containing relevant individual, household and partner level measures. The findings and conclusions from this analysis were detailed in that chapter and are briefly reiterated here, with the aim of later considering them alongside the results of this chapter.

### 4.5.1 Predictors of the timing of older women’s employment exit

Firstly, we found no statistically significant evidence that male partner health influences older women’s likelihood of labour market exit. However this came with a caveat in that this result is a possible manifestation of two competing theories with regards to women’s work in the advent of poor partner health. In some instances employed women may leave work to provide necessary care, but alternatively they may remain in employment to ensure the financial wellbeing of the family. These competing behaviours could explain the insignificant result of partner health on predicting the timing of women’s employment exit - in which case
concluding that this factor has no impact on women’s work would be erroneous. Rather, the influence of partner health in the previous chapter was raised as an area requiring more in depth analysis of couples with a wider range of health and income circumstances.

Evidence was found, in the analysis of Chapter 3, for the influence of the male partner’s employment status on the timing of older women’s exit from work. Women coupled to retired men have an estimated probability of leaving work that is 57.8% higher than those with employed partners, whereas the risk differential of having a spouse in an alternative not working but non retired state is approximately 18.5%. The accrued pension resources of the couple, however, were found to have no effect on the timing of women’s transitions with respondents from pension wealth quintile groups having equally likely probability of transitioning out of work.

4.5.2 Predictors of voluntary and involuntary pathways

The focus of this chapter is on the second research hypothesis, which relates to the influence of partner health and pension wealth on the type of any older woman’s transition that occurs between the age of 50 and eligibility for the state pension. Two types of event were considered; involuntary exit into self reported illness, unemployment or a caring role and voluntary exit into reported retirement. It was hypothesised that household pension wealth has a greater impact on voluntary than involuntary labour market exit, with involuntary transitions influenced more by the health status of either a woman or her partner. In the ELSA sample of 1569 women selected for this research 134 women (8.5%) experienced a voluntary retirement with 153 (9.8%) designated as having an involuntary exit. A logistic regression model was fitted for comparing the odds of each type of transition for different levels of partner health, employment status and pension wealth.

Results show that the type of transition that occurs is determined by pension resources, with the wealthiest women least likely to experience involuntary exit and more likely to exit into voluntary early reported retirement. Women with the lowest levels of pension wealth, in contrast, are an estimated 5.9 times more likely to have an involuntary exit compared to those in the wealthiest quintile. With regards to health, and neither a woman’s own health or that of her partner impact on her odds of involuntary transition; women in poor health, or
coupled to a man with a limiting condition, are as likely to exit involuntarily as voluntarily.

### 4.5.3 The interaction between the domestic context and older women’s employment transitions and pathways

Here we bring together the results of Chapter 3 and this one to provide an overall summary of the interaction between the domestic context and older women’s employment trajectories. The analysis in Chapter 3 determined how the risk of exit differs between women residing in different household circumstances, whilst the conclusions of this chapter explain how the subsequent labour market position varies across respondents. This is explained further with reference to Figure 4.6. This diagram shows the significant predictors of older women’s employment exit as well as influential factors for each of the involuntary and voluntary pathway. In addition to the above results that directly relate to the research questions, we consider those concerning women’s caring responsibilities, income and housing status.

**Figure 4.6: Older women’s pathways to retirement**

Of interest in Figure 4.6 is the disparate effect that women’s individual and domestic circumstances have on the two studied aspects of their employment trajectory. Poor health, for example, determines the timing of a woman’s transition, but is not associated with involuntary exit; this implies that those in poor health are at higher risk of leaving work, but are subsequently equally likely to report as retired as they are any other non-working state. The same applies for women with caring responsibilities. Their likely age of exit is influenced by having a caring role, but this does not determine whether she reports as either retired or an involuntary state. Rather, the financial factors of income and household pension wealth
determine the voluntary or involuntary nature of any exit; low income earners and those with the lowest level of pension resources tend to experience involuntary transitions whereas high income and pension resources are associated with reported retirement prior to state pension age. The influence of these financial factors is limited to the type of transition that occurs with neither income nor pension wealth predicting the age of exit.

One aspect of the domestic environment that does impact on both the timing and type of an older woman’s employment trajectory is the labour market status of her partner or spouse. Women are at greater risk of exit if their partner is not working and, additionally, her subsequent pathway is determined by his specific status. Having a retired partner increases the probability that an older woman leaves work prior to state pension age by an estimated 57.8%, and she is most likely to follow the voluntary exit pathway. Involuntary transitions, in contrast, tend to occur amongst women with spouses that are also in one of the designated involuntary states. A not working, not retired partner increases the risk of older woman’s exit by an estimated 18.5% and she is an estimated 1.8 times more likely to take an involuntary rather than voluntary pathway to retirement. The influence of the male partner is unique in this respect - other studied attributes determine either the timing or type of the female spouse’s transition, but not both.

The findings summarised here identify and quantify the specific aspects of the domestic context that influence an older woman’s employment trajectory. Later, in Chapter 7, these results will be developed further with reference to existing literature surrounding the retirement patterns of women and their partners. Prior to this, we develop a more thorough understanding of the employment transitions of the male partners within our studied couples. The third research question references the asymmetric effect of health conditions on the employment of the other spouse, and analysis relating to this is presented next, in Chapter 5.
Chapter 5

Partner employment transitions

5.1 Introduction

The aim of this research is to study older women’s retirement trajectories within the wider domestic context. The first hypothesis concerns the impact of male partner health and employment status, and household pension wealth, on the probability of women’s employment exit in the ten years prior to state pension age. This was addressed in Chapter 3. The determinants of voluntary and involuntary transitions were the focus of Chapter 4; analysis presented there addressed the second research question, which asks whether the impact of male partner health and pension wealth on women’s employment differs across voluntary and involuntary pathways.

From this earlier work we have established that women with a non-working partner, caring responsibilities, poor health and part time working patterns are at greater risk of leaving employment. Household financial factors do not predict the timing of a woman’s exit from work, but do determine the nature of the pathway followed after any transition. Those at the lower end of the pension wealth and income distributions are more likely to take the involuntary route, with voluntary retirement prior to state pension age predicted for those with the highest level of household accumulated pension resources or high earning women.

No evidence was found for the impact of male partner health on women’s likelihood of exit, but this may be a reflection of two opposing effects that poor partner health can have on women’s work. In the advent of poor spousal health a woman may leave employment to provide necessary care or alternatively, she may remain in work to ensure the financial
wellbeing of the family. These conflicting outcomes may preclude any statistically significant finding that relates male partner health to women’s transitions. The particular labour market position of the male spouse does determine the pathway an older woman is likely to take to retirement. Women partnered to retired men are more likely to experience a voluntary transition and report as retired prior to state pension age, whereas women coupled to men in alternative non working inactive states are at greater risk of involuntary exit.

In this chapter the third research question of this thesis is addressed. This focuses on partner health and whether it’s effect on the conditional probability of an employment transition differs for older women and their partners. As explained above, no evidence was found in earlier analysis to support the hypothesis that poor health of the male partner impacts on the female member’s risk of transition. Here, we consider cross-spousal effects of health and the influence of the female partner on the male spouse’s probability of continued employment. Formally this third research hypothesis is stated as follows:

**Research question 3** Does partner health impact equally on the probability of continued employment for older women and their male partners?

**Hypothesis 3** Partner health has a greater impact on the probability of a coupled older woman leaving work than it does on the transition probability of the male partner.

Note that analysis in this chapter will be conducted on a smaller subset of the original sample. Whilst 1569 couples were analysed in Chapter 3 for women’s transitions only 1230 of these couples are studied here. This is due to missing data in male partner covariate values. The next section contains descriptive statistics relating to the male partners from these households, the modelling approach is detailed in Section 5.3 and results follow in Section 5.4. This chapter concludes with a comparison of findings from both the analysis of women’s transitions and the male partners together, in Section 5.6.
5.2 Descriptive analysis of male partner data

The analysis of women’s employment trajectories was based on a sample of 1569 households with 287 observed transitions, giving a transition rate of 18.3%. However not all of these families are analysed a second time for the men’s transitions; 339 are excluded due to missing data in the male partner covariate measures. This leaves a sample of 1230 men with 181 observed exits and a transition rate of 14.7%. Descriptive statistics relating to these men were presented in Chapter 2 alongside those for the female partners. Here, we give details of how the observed transition rates for the male partners differ according to their individual and household characteristics. Figures are calculated from the person-period dataset that subsequent models will be fitted to; this contains 4701 records with one per year of observation. In Section 5.2.1 the trend in men’s observed transition rates over time is described and statistics relating to their health and other individual level attributes follow that. Household factors of wealth and tenure are considered in Section 5.2.3 with the health of female partners described in Section 5.2.4.

5.2.1 Observed transition rates over time

The first stage in analysing the male partner employment data is to establish the trend in sample transition rates over time and how this compares to that observed for the female couple members. The metric for time in the analysis of partner transitions is the female partner’s age. The decision to structure time in this way reflects the overall aim of the thesis, which is to examine the relationship between older women’s employment transitions and their domestic context; it is not to provide an in depth analysis of men’s retirement trajectories. Modelling the transitions of male partners relative to women’s age will provide contextual information on the circumstances within the households where women’s retirement trajectories unfold.

Table 5.1 shows the age distribution for the 1230 sampled men as of their first observation. Twenty seven were aged 44 or younger; this was 2.2% of the sample, with 46.7% aged between 45 and 54 inclusive. These men were at least ten years away from their state pension age of 65. Fifty percent of the male partners were aged between 55 and 64 and were within ten years of pension eligibility. This is not, therefore, a sample of men that could be
considered approaching retirement in the same way as the studied women are. Rather, the analysis of male partners will provide information about their employment transitions that in turn could impact on the labour market position of their female spouse.

Table 5.1: Distribution of observed ages for male partner sample

<table>
<thead>
<tr>
<th>Age of male partner on entry</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 45</td>
<td>27</td>
</tr>
<tr>
<td>45 - 54</td>
<td>575</td>
</tr>
<tr>
<td>55 - 64</td>
<td>615</td>
</tr>
<tr>
<td>65 - 74</td>
<td>12</td>
</tr>
<tr>
<td>75 and over</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>1230</td>
</tr>
</tbody>
</table>

Table 5.1 contains sample transition rates for both older women and their spouses according to the female’s age. In households with a resident 51 year old female 3.3% of women left work and 1.8% of the male partners transitioned. In couples with a 52 year old female member 2.5% of women left compared to 3.5% of men, and so on as stated in the table. These proportions are plotted in Figure 5.1 and show an increasing trend in both male and female transitions. There is, however, a notably steeper increase in women’s transitions over time. This reflects the wider range of male partner ages as described above; the older men that are included in the male partner sample are further from state pension age than the studied women and hence may be less likely to transition from work. The mean age of men with an observed transition is 59.4 years compared to 56.5 years for their counterparts with no recorded exit.

Table 5.2: Observed transition rate by woman’s age and gender

<table>
<thead>
<tr>
<th>Woman’s age</th>
<th>Female partners (%)</th>
<th>Male partners (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>51</td>
<td>3.3</td>
<td>1.8</td>
</tr>
<tr>
<td>52</td>
<td>2.5</td>
<td>3.5</td>
</tr>
<tr>
<td>53</td>
<td>2.1</td>
<td>2.4</td>
</tr>
<tr>
<td>54</td>
<td>3.9</td>
<td>5.2</td>
</tr>
<tr>
<td>55</td>
<td>4.0</td>
<td>3.6</td>
</tr>
<tr>
<td>56</td>
<td>4.7</td>
<td>4.9</td>
</tr>
<tr>
<td>57</td>
<td>5.8</td>
<td>3.8</td>
</tr>
<tr>
<td>58</td>
<td>7.8</td>
<td>5.0</td>
</tr>
<tr>
<td>59</td>
<td>9.0</td>
<td>4.6</td>
</tr>
</tbody>
</table>

5.2.2 Male partner individual characteristics

The research question addressed in this chapter is concerned with the effect of partner’s health on the other spouse’s continued employment. Measures of health are therefore of primary interest, but to isolate their effect adjustments are made for a number of other factors.
We control for the influence of men’s age, income and working patterns, education and social class, dependent children and caring responsibilities before focusing on the health measures.

**Control factors: income, education, social class, dependent children**

Table 5.3 (page 187) contains observed sample transition rates for all male partners differentiated by education level, social class and dependent children. Men with at least the equivalent of A level education - that is, the highest qualification group - have the highest observed transition rate with 4.4% leaving work. Those with the lowest level of qualification, which is less than O level equivalent, have observed rates of 3.4%, whilst 3.6% of men with mid level qualifications have a recorded transition.

There is greater disparity in the sample transition rates between men from different social class backgrounds. Routine and manual workers have the highest incidence of transition with 4.6% having left work compared to 2.6% of intermediate level workers and 3.7% of those from a professional class. There is minimal difference in the observed rates between men residing in households with children present and those without, at 3.9% and 3.8% respectively.

The mean weekly income amongst the subgroup of male partners who left work is £419.10 compared to £419.20 for the continually employed partners. This suggests that there may not be any relationship between men’s income and their probability of transitioning.
Table 5.3: Distribution of observed male partner transitions for control variables

<table>
<thead>
<tr>
<th>Education</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than O level</td>
<td>3.4</td>
<td>3.6</td>
<td>4.4</td>
<td>4.6</td>
<td>2.6</td>
<td>3.7</td>
<td>3.9</td>
<td>3.8</td>
<td>3.9</td>
<td>3.8</td>
</tr>
<tr>
<td>O level equivalent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A level or higher</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5.4: Distribution of observed male partner transitions according to individual level attributes

<table>
<thead>
<tr>
<th>Working hours</th>
<th>Provides care</th>
<th>Limiting health</th>
<th>Self rated health</th>
<th>Decline in health</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full time</td>
<td>Part time</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Transition rate (%)</td>
<td>3.3</td>
<td>7.6</td>
<td>3.8</td>
<td>4.2</td>
</tr>
</tbody>
</table>
Working hours, caring responsibilities and health

Figures in Table 5.4 show how the observed transition rates for the male partners from the studied households vary between full and part time employees, for men with caring responsibilities and according to health status. The rate of employment exit amongst those who work part time is 7.6% and this is more than double that recorded for full time employees, with a rate of 3.3%. There is less discrepancy between men who have recently provided care and their peers who have not had caring duties with observed rates of exit of 4.2% and 3.8% respectively.

Three binary measures of the male partner’s health are considered - the presence of a limiting health condition, self rated health and a decline in health status. The proportion of men with a limiting health condition who left work is nearly double that of men with no such limitation; transition rates are 6.3% and 3.4% for each of these groups, which suggests that men’s health limitations are associated with higher probability of labour market exit. The difference in transition rates between men with regards to the self rated health measure is less pronounced. Those that have described their health as good or better have an observed transition rate of 3.8% compared to 4.8% for men with poor self rated health. The third indicator is for deterioration in health status. This measure is positive for a respondent if there is an observed change from no limiting health condition to having one present. Men without a positive indicator for this measure are considered to have consistent or improving health status and, from the figures given in Table 5.4, this group have a lower observed transition rate than men with a recorded deterioration. Whereas 5.2% of men with decline in health left employment, 3.8% of men with stable or improved health did so. Whether the differences in sample transition rates between groups of men defined by these varying health states are statistically significant is considered in the modelling process which follows this initial exploratory analysis.

5.2.3 Household factors

Two wealth measures - of pension wealth and non pension wealth - are considered with housing status also of interest. These three covariates are household measures and as such, the male partners are allocated the same value for each as their female partner was in the
analysis of women’s transitions. Both wealth indicators are structured as categorical variables based on quintile groups. Quintiles are calculated relative to households with women of the same age, using the total amount of wealth accumulated at the time of the couple’s last observation. For each measure figures in Table 5.5 show the proportion of men from the given quintile group who left work. There is an apparent positive association between transition rate and pension wealth with observed rates of 2.6%, 3.2% and 6.1% for the poorest, middle and wealthiest groups respectively. The relationship between non pension wealth and transition rates is less clear; the highest incidence of exit is observed within the wealthiest quintile group, but it is men from the fourth quintile that have the lowest rate of 3.4%.

The couples in this study are allocated to one of three categories for housing status. They are designated as either owning their home outright, having an outstanding mortgage or as renting. The proportion of men from each type of household that left work is given in Table 5.5. Men in homes owned outright have a higher observed transition rate of 5.5% compared to 3.0% for those with mortgages owning and 3.6% of renters.

### 5.2.4 Female partner factors

In the analysis of women’s transitions in Chapter 3 both the health of the male partner as well as their employment status were included as potentially influential factors on the conditional probability of exit. Whilst no evidence was found to support the hypothesis that male partner health impacts on women’s transition rates, their employment status was established as a significant predictor. The study of the male partners’ transitions differs here in that it is not possible to examine the influence of women’s employment on the probability that their spouse leaves work. The households in this study were selected if they contained a working woman at baseline and observation of the family ceased when that woman either left work or was censored. Female partners are, therefore, only observed when they were employed and this precludes any consideration of how different women’s employment states might impact on male partner transitions. Given this, the only female partner covariate considered is that of limiting health, although income is entered as a control measure. In couples with women suffering from a limiting health condition 3.9% of the male partners left employment. This is only marginally higher than the transition rate of 3.8% observed in couples where the female
Table 5.5: Distribution of observed male partner transitions for household level wealth variables

<table>
<thead>
<tr>
<th>Pension wealth quintile</th>
<th>Non pension wealth quintile</th>
<th>Housing status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poorest</td>
<td>2.6 2.8 3.2 4.5 6.1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3.4 4.3 3.8 2.8 4.8</td>
<td>5.5</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>3.0</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>3.6</td>
</tr>
<tr>
<td>Richest</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
member had no such health condition. The median weekly income of the older women in the male partner sample is £203 with mean £241.

5.3 Modelling approach and strategy

A series of discrete time event history models are constructed to predict the male partner transitions out of employment. These models take the form of Equation 2.1 that was first presented in Chapter 2, and is reproduced for convenience here as Equation 5.1. The outcome measure used in this specification is the conditional probability that male \( i \) transitions out of work at time \( t \); this is denoted by \( p_{it} \). Time is measured as the female partner’s age, with a range of 50 to 59 years. The baseline hazard function is given by \( \alpha^T z_{it} \) and describes how the conditional probability that a man leaves work changes as his partner ages. Covariates are contained in \( x_{it} \) with corresponding coefficients in \( \beta \).

\[
\log(-\log(1 - p_{it})) = \alpha^T z_{it} + \beta^T x_{it} \tag{5.1}
\]

The event history models for the male partner employment transitions are fitted separately from those of the female couple members - the transitions of both partners are not modelled jointly. This decision was first justified and explained in Chapter 2; to summarize, considering partner transitions simultaneously would require either modelling events across a prohibitively wide age range or restricting the sample to dual worker households comprised of two employed persons. Because of these limitations the decision was made to construct two separate series of models - one for women’s transitions and one for those of the male partners from the same households. The models for predicting female partner transitions were presented in Chapter 3 and examined the impact of male partner and household covariates on the conditional probability of older women’s labour force exit. An independent series of models for studying the effect of women’s characteristics on the male partner’s employment are constructed in this chapter. However, whilst models for men’s and women’s transitions are estimated separately, the trajectories for the male partner’s employment are constructed along a time frame that is parallel to that of the female member. The earlier analysis of the female partner transitions modelled their labour force exit between the ages
of 50 and 59 and now we consider the employment behaviour of their male spouses during this same time frame.

5.3.1 Covariate measures

An in depth description of covariate measures was given in the methods presentation of Chapter 2, and descriptive analysis of the observed male partner transition rates for the attributes of interest detailed above in Section 5.2. To briefly summarise, the male partner control measures are age, income, education, social class and having a dependent child. Income is time varying and takes a log transformed continuous form, whereas education and social class are each structured as time invariant categorical variables with three groups. The reference category for education is the lowest level of less than O level equivalent. The two alternative groups are those with O level or equivalent and higher than A level, which includes post secondary qualifications. The reference group for social class is men with managerial or professional occupations with the two alternatives being intermediate and routine/manual occupations. A dependent child is indicated if under 17 years and earning less than £5000 per year. This is also a time invariant measure.

Part time working is defined as less than 35 hours per week and represented with a binary indicator that has full time as the reference. The presence of a limiting health condition is also configured as a binary variable. Self rated health has two categories; ‘good or better’ forms the reference with ‘poor’ the alternative. A deterioration in health status indicates a decline in either of these measures, against a reference group of stable or improving health. Caring responsibilities are incorporated with a binary indicator that signifies whether a respondent has recently provided care. There are three household level covariates of pension wealth, non pension wealth and tenure. For each variable the male spouse is allocated the same value or status as his wife or female partner. The wealth variables both have five categories with the richest quintile forming the reference group. Quintiles are calculated with reference to women of the same age; that is, women of the same year of age are ranked and then divided into one of five groups according to the level of wealth accumulated at that point. The pension measure includes wealth from state and private sources, whilst non pension wealth encompasses property assets, business value and other financial resources. Housing status is
a categorical measure with respondents designated as either renting, having an outstanding mortgage or those who own their homes outright. This third group is the reference category. Each of the covariates listed here - part time working, health and wealth - are time varying.

Two time varying indicators of the female partner’s circumstances are included in this analysis. Weekly income is a log transformed continuous measure, whilst a limiting health condition is indicated with a binary variable. All women in the studied households are in employment and this precludes any analysis of the impact that differing spousal labour market positions might have on the male partner’s employment transitions. There is, consequently, no spousal employment status covariate in the male partner model as there is for the analysis of female partner transitions.

## 5.4 Results

Results from fitting a series of event history specifications for the male partner employment transitions are presented in this section. The baseline hazard function is constructed first with covariate measures introduced in subsequent stages.

### 5.4.1 The baseline hazard function

Earlier analysis of couple member’s transition rates showed that women aged between 50 and 59 are more likely to leave work the older they are. The trend for the male partners was less distinct with a flatter, although still positive, gradient in observed transition rates over time. In this section we formally establish a relationship between women’s age and their male partners’ transition rates with the estimation of the baseline hazard function. A general form is fitted first in which the hazard can vary at each time point. This version will provide the most accurate estimated transition rates, but requires nine terms to do so; the estimated coefficients and confidence intervals for these terms are given in Table 5.6, Model 1. Adopting this form of baseline hazard has consequences when predictors are entered at a later stage. Determining the influence of covariates is straightforward if they are entered as a main effect, but testing for any change in covariate impact over time requires fitting interaction terms with the age variables. This is not feasible if there are nine age variables.
Table 5.6: Parameter estimates for the baseline hazard function from discrete time event history models for the conditional probability of male partner transitions from employment

<table>
<thead>
<tr>
<th></th>
<th>General specification</th>
<th>Linear baseline</th>
<th>Quadratic baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Binary age indicators</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female partner age 51</td>
<td>-4.032***</td>
<td>-4.032***</td>
<td>-4.032***</td>
</tr>
<tr>
<td>Female partner age 52</td>
<td>-3.327***</td>
<td>-3.327***</td>
<td>-3.327***</td>
</tr>
<tr>
<td></td>
<td>(-3.777,-2.878)</td>
<td>(-3.777,-2.878)</td>
<td>(-3.777,-2.878)</td>
</tr>
<tr>
<td>Female partner age 53</td>
<td>-3.703***</td>
<td>-3.703***</td>
<td>-3.703***</td>
</tr>
<tr>
<td></td>
<td>(-4.209,-3.197)</td>
<td>(-4.209,-3.197)</td>
<td>(-4.209,-3.197)</td>
</tr>
<tr>
<td>Female partner age 54</td>
<td>-2.933***</td>
<td>-2.933***</td>
<td>-2.933***</td>
</tr>
<tr>
<td></td>
<td>(-3.279,-2.586)</td>
<td>(-3.279,-2.586)</td>
<td>(-3.279,-2.586)</td>
</tr>
<tr>
<td>Female partner age 55</td>
<td>-3.301***</td>
<td>-3.301***</td>
<td>-3.301***</td>
</tr>
<tr>
<td></td>
<td>(-3.719,-2.883)</td>
<td>(-3.719,-2.883)</td>
<td>(-3.719,-2.883)</td>
</tr>
<tr>
<td>Female partner age 56</td>
<td>-2.983***</td>
<td>-2.983***</td>
<td>-2.983***</td>
</tr>
<tr>
<td></td>
<td>(-3.353,-2.613)</td>
<td>(-3.353,-2.613)</td>
<td>(-3.353,-2.613)</td>
</tr>
<tr>
<td>Female partner age 57</td>
<td>-3.258***</td>
<td>-3.258***</td>
<td>-3.258***</td>
</tr>
<tr>
<td></td>
<td>(-3.696,-2.820)</td>
<td>(-3.696,-2.820)</td>
<td>(-3.696,-2.820)</td>
</tr>
<tr>
<td>Female partner age 58</td>
<td>-2.977***</td>
<td>-2.977***</td>
<td>-2.977***</td>
</tr>
<tr>
<td></td>
<td>(-3.386,-2.568)</td>
<td>(-3.386,-2.568)</td>
<td>(-3.386,-2.568)</td>
</tr>
<tr>
<td>Female partner age 59</td>
<td>-3.061***</td>
<td>-3.061***</td>
<td>-3.061***</td>
</tr>
<tr>
<td></td>
<td>(-3.585,-2.537)</td>
<td>(-3.585,-2.537)</td>
<td>(-3.585,-2.537)</td>
</tr>
<tr>
<td><strong>Continuous age variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female partner age</td>
<td>0.081***</td>
<td>0.081***</td>
<td>0.081***</td>
</tr>
<tr>
<td></td>
<td>(0.020,0.142)</td>
<td>(0.001,0.590)</td>
<td>(0.001,0.590)</td>
</tr>
<tr>
<td>Female partner age(^2)</td>
<td>-0.021</td>
<td>-0.021</td>
<td>-0.021</td>
</tr>
<tr>
<td></td>
<td>(-0.049,0.007)</td>
<td>(-0.049,0.007)</td>
<td>(-0.049,0.007)</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.644***</td>
<td>-4.076***</td>
<td>-4.076***</td>
</tr>
<tr>
<td></td>
<td>(-3.996,-3.292)</td>
<td>(-4.772,-3.381)</td>
<td>(-4.772,-3.381)</td>
</tr>
</tbody>
</table>

| Observations         | 4,701                  | 4,701           | 4,701              |
| Log Likelihood       | -758.502               | -763.586        | -762.476           |
| Akaike Inf. Crit.    | 1,535.003              | 1,531.171       | 1,530.953          |

*Note:* *p*<0.1; **p**<0.05; ***p**<0.01

with which to interact.

An alternative linear form for the fitted baseline hazard function is given in Table 5.6, Model 2. The estimated coefficient for time in this specification is 0.081 and as a positive term it reflects the increasing trend in observed transition rates described earlier. Given that time in this model is given relative to the female partner's age, the model predicts that the conditional probability of a man leaving work increases by 0.081 on the cloglog scale for every year that his spouse ages between 50 and 59. This converts to a probability of 8.4%.

Whilst this linear specification does not fit the observed data as well as the general version -
as evidenced by the respective log likelihood values of -758.502 and -763.586 - it is a more parsimonious model. An additional quadratic term for time is tested (Table 5.6, Model 3), but not found to be statistically significant ($\chi^2(1) = 2.2186, p = 0.1364$). Given the results presented here, a linear function is adopted as the baseline hazard for the men’s transitions.

### 5.4.2 Male partner individual level predictors

Individual level measures are added to the linear baseline hazard function. Control factors including income, education and social class are incorporated first with the introduction of working hours, caring and health covariates following that.

**Control factors: age, income, education, social class, children**

Indicators of the male partner’s age and income, education, social class status and dependent children are added to the linear baseline hazard function. Results are given in Table 5.7, Model 1 on page 197 and are summarized here. They are entered as control variables and are therefore retained in the model irrespective of the statistical significance of each; as a group they significantly improve the fit of the model ($\chi^2(7) = 91.474, p < 0.001$).

Men’s age is entered in continuous form and has an estimated coefficient of 0.170 on the cloglog scale. The conditional probability of the male partner leaving work is therefore predicted to increase by 18.5% per year; this is commensurate with expectations from earlier descriptive analysis. A positive relationship between men’s income and their estimated hazard is also established, but the effect is minimal with this variable not statistically significant if considered separately from the other control measures.

The effect of education on male partner’s predicted transition rates is also relatively small. The education covariate is structured in a categorical form with the reference category comprised of men with the lowest level of education (lower than O level equivalent). Compared to them, men with mid level education have a 6% higher estimated probability of leaving work and the hazard for those in the highest qualification group is raised by 7.7%. However, as with the income variable, education is not a statistically significant predictor when considered separately from the other control variables.

Men are organised into one of three social class groups of routine/manual, intermediate
and the reference category of managerial/professional. Results from the fitted model indicate that men from the intermediate social class group have a predicted probability of leaving work that is 55.2% lower than that for managerial/professional workers. The estimated hazard for the routine/manual group is 31.3% lower.

There is no impact on the conditional probability of exit for men if he has a dependent child. The estimated coefficient of -0.001 indicates that the presence of children does not influence the male partner’s chances of staying in work.

**Working hours, caring responsibilities and health**

Indicators for part time working hours, caring responsibilities and health are incorporated separately into the model containing the individual level control variables and results are given in Table 5.7, Models 2 - 6. The effect of part time working is statistically significant ($\chi^2(1) = 4.5028, p = 0.03384$) with an estimated coefficient of 0.414 on the cloglog scale. Part time working, therefore, is associated with a 51.3% increase in risk of transition of a male partner compared to his full time counterpart. The effect of having caring duties is not significant ($\chi^2(1) = 0.8098, p = 0.3682$); a male providing care has a similar estimated hazard as a man with no such responsibilities. This variable is therefore not retained in the model.

Initial analysis of health measures presented in Section 5.2.2 showed a higher rate of event occurrence amongst men with limiting health conditions, with poor self rated health and for men who experience a deterioration in health. Having a limiting health condition is a significant predictor of transition ($\chi^2(1) = 8.1868, p = 0.00422$), but poor self rated health is not ($\chi^2(1) = 0.9869, p = 0.3205$). The covariate for deterioration in health status is also not statistically significant ($\chi^2(1) = 0.0093, p = 0.9233$). Of the three health indicators, therefore, that for limiting health is retained in the model, but self rated health and deterioration in health are not.

**5.4.2.1 Interaction effects**

Part time working patterns and having a limiting health condition are significant predictors of the male partner transitioning out of work. However these measures are currently assumed
Table 5.7: Parameter estimates from discrete time event history models for the conditional probability of male partner transitions from employment, with individual level covariates

<table>
<thead>
<tr>
<th>Control variables</th>
<th>Part time</th>
<th>Caring</th>
<th>Limiting health</th>
<th>Self rated</th>
<th>Decline in health</th>
<th>Interaction terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female partner’s age</td>
<td>-0.020</td>
<td>-0.018</td>
<td>-0.021</td>
<td>-0.015</td>
<td>-0.021</td>
<td>-0.021</td>
</tr>
<tr>
<td>(0.085, 0.044)</td>
<td>(0.082, 0.047)</td>
<td>(0.085, 0.044)</td>
<td>(0.080, 0.049)</td>
<td>(0.086, 0.043)</td>
<td>(0.085, 0.044)</td>
<td>(0.106, 0.025)</td>
</tr>
<tr>
<td>Male partner’s age (mean centred)</td>
<td>0.170***</td>
<td>0.157***</td>
<td>0.171***</td>
<td>0.162***</td>
<td>0.171***</td>
<td>0.230***</td>
</tr>
<tr>
<td>(0.135, 0.206)</td>
<td>(0.120, 0.194)</td>
<td>(0.136, 0.207)</td>
<td>(0.127, 0.198)</td>
<td>(0.135, 0.206)</td>
<td>(0.135, 0.206)</td>
<td>(0.180, 0.279)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>0.013</td>
<td>0.017</td>
<td>0.012</td>
<td>0.010</td>
<td>0.013</td>
<td>0.032</td>
</tr>
<tr>
<td>(-0.094, 0.120)</td>
<td>(-0.091, 0.125)</td>
<td>(-0.095, 0.119)</td>
<td>(-0.096, 0.117)</td>
<td>(-0.094, 0.120)</td>
<td>(-0.094, 0.120)</td>
<td>(-0.080, 0.145)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td>0.058</td>
<td>0.054</td>
<td>0.063</td>
<td>0.070</td>
<td>0.069</td>
<td>0.057</td>
</tr>
<tr>
<td>(0.341, 0.457)</td>
<td>(0.345, 0.454)</td>
<td>(0.336, 0.462)</td>
<td>(0.330, 0.471)</td>
<td>(0.331, 0.468)</td>
<td>(0.342, 0.456)</td>
<td>(0.397, 0.399)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>0.074</td>
<td>0.055</td>
<td>0.071</td>
<td>0.097</td>
<td>0.090</td>
<td>0.074</td>
</tr>
<tr>
<td>(-0.323, 0.471)</td>
<td>(-0.344, 0.455)</td>
<td>(-0.326, 0.468)</td>
<td>(-0.303, 0.496)</td>
<td>(-0.309, 0.489)</td>
<td>(-0.323, 0.471)</td>
<td>(-0.389, 0.406)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td>-0.802***</td>
<td>-0.817***</td>
<td>-0.786***</td>
<td>-0.804***</td>
<td>-0.802***</td>
<td>-0.885***</td>
</tr>
<tr>
<td>(1.261, -0.343)</td>
<td>(1.276, -0.358)</td>
<td>(1.261, -0.343)</td>
<td>(1.265, -0.328)</td>
<td>(1.263, -0.345)</td>
<td>(1.261, -0.342)</td>
<td>(-1.348, -0.421)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.375**</td>
<td>-0.376**</td>
<td>-0.392**</td>
<td>-0.375**</td>
<td>-0.376**</td>
<td>-0.409**</td>
</tr>
<tr>
<td>(-0.732, -0.018)</td>
<td>(-0.734, -0.018)</td>
<td>(-0.732, -0.019)</td>
<td>(-0.751, -0.033)</td>
<td>(-0.741, -0.026)</td>
<td>(-0.732, -0.018)</td>
<td>(-0.760, -0.050)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.001</td>
<td>-0.009</td>
<td>0.002</td>
<td>-0.017</td>
<td>-0.004</td>
<td>-0.002</td>
</tr>
<tr>
<td>(-0.373, 0.371)</td>
<td>(-0.380, 0.363)</td>
<td>(-0.370, 0.374)</td>
<td>(-0.390, 0.356)</td>
<td>(-0.376, 0.368)</td>
<td>(-0.374, 0.370)</td>
<td>(-0.401, 0.343)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>0.414**</td>
<td>0.748***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.043, 0.784)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age: part time</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.253</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(-0.278, 0.783)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.526***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.181, 0.876)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age: limiting health condition</td>
<td>0.876***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.486, 1.257)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.257</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.234, 0.748)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decline in health (ref: constant health status)</td>
<td>0.032</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.614, 0.677)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,701</td>
<td>4,701</td>
<td>4,701</td>
<td>4,701</td>
<td>4,701</td>
<td>4,701</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-717.849</td>
<td>-715.597</td>
<td>-717.444</td>
<td>-713.755</td>
<td>-717.355</td>
<td>-717.844</td>
</tr>
<tr>
<td>Akaiake Inf. Crit.</td>
<td>1,453.697</td>
<td>1,451.194</td>
<td>1,454.887</td>
<td>1,447.510</td>
<td>1,454.710</td>
<td>1,458.688</td>
</tr>
<tr>
<td>1,429.140</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
to have a proportional impact on the hazard in that the effect of each is assumed constant irrespective of the man’s age. Interaction terms for part time working and men’s age, and limiting health and men’s age are added to the model that contains indicators for both of these as main effects. Table 5.7, Model 7 shows the results. Both interaction terms are statistically significant ($\chi^2(2) = 21.024, p < 0.001$) and this indicates that the effect of having a limiting health condition or part time working does change over time. The estimated coefficient for the health and age interaction term is $-0.137$ on the cloglog scale. The risk of transitioning for a male partner with a limiting health condition decreases by 12.8% per year of age. The effect over time of working part time is similarly negative, but the impact is lower with an estimated 8.6% reduction in hazard per year.

### 5.4.3 Household level predictors of male partner transitions

Three household level measures are considered in this research - pension wealth, non pension wealth and tenure. Each takes a categorical structure with the wealth variables comprised of five quintile groups and tenure having three options of owning outright, outstanding mortgage or renting. Each variable is added separately to the model with individual level variables and estimated coefficients in Table 5.8.

Descriptive analysis presented in Section 5.2.3 showed a positive relationship between pension wealth and the probability of transitioning with higher rates of exit observed amongst men from the wealthiest households. The pension wealth variable does improve model fit (Table 5.8, Model 1; $\chi^2(4) = 9.5081, p = 0.04958$) and the estimated coefficients reflect the relationship observed in the descriptive analysis. Men in the wealthiest quintile group are at greatest risk of leaving work. Compared to them, those with the lowest accumulated pension wealth are an estimated 45.2% less likely to transition and men in the middle quintile are approximately 43.2% less likely to exit.

Non pension wealth is also found to be a significant predictor of male partner transitions (Table 5.8, Model 2; $\chi^2(4) = 10.435, p = 0.03371$). However it is men from the second poorest quintile group that have the highest estimated probability of leaving; they have a predicted hazard that is 11.4% higher than men in the wealthiest group. Male partners from households in the fourth quintile, which is the second wealthiest group, have the lowest
<table>
<thead>
<tr>
<th></th>
<th>Pension wealth (1)</th>
<th>Non pension wealth (2)</th>
<th>Tenure (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female partner’s age</td>
<td>-0.037</td>
<td>-0.043</td>
<td>-0.037</td>
</tr>
<tr>
<td></td>
<td>(-0.102,0.029)</td>
<td>(-0.109,0.023)</td>
<td>(-0.102,0.029)</td>
</tr>
<tr>
<td>Male partner’s age (mean centred)</td>
<td>0.227***</td>
<td>0.233***</td>
<td>0.220***</td>
</tr>
<tr>
<td></td>
<td>(0.177,0.277)</td>
<td>(0.183,0.282)</td>
<td>(0.170,0.270)</td>
</tr>
<tr>
<td>Male partner’s income (log)</td>
<td>0.005</td>
<td>0.031</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>(-0.102,0.113)</td>
<td>(-0.083,0.145)</td>
<td>(-0.085,0.141)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.070</td>
<td>0.021</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>(-0.472,0.332)</td>
<td>(-0.382,0.424)</td>
<td>(-0.392,0.410)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>-0.162</td>
<td>0.008</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(-0.576,0.252)</td>
<td>(-0.404,0.419)</td>
<td>(-0.394,0.405)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>-0.675***</td>
<td>-0.974***</td>
<td>-0.931***</td>
</tr>
<tr>
<td></td>
<td>(-1.162,-0.188)</td>
<td>(-1.442,-0.506)</td>
<td>(-1.395,-0.467)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.214</td>
<td>-0.430**</td>
<td>-0.417**</td>
</tr>
<tr>
<td></td>
<td>(-0.591,0.164)</td>
<td>(-0.802,-0.058)</td>
<td>(-0.772,-0.061)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.042</td>
<td>-0.022</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(-0.414,0.330)</td>
<td>(-0.397,0.352)</td>
<td>(-0.366,0.379)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>0.779***</td>
<td>0.721***</td>
<td>0.721***</td>
</tr>
<tr>
<td></td>
<td>(0.337,1.222)</td>
<td>(0.277,1.165)</td>
<td>(0.281,1.162)</td>
</tr>
<tr>
<td>Male partner age:part time</td>
<td>-0.099**</td>
<td>-0.084**</td>
<td>-0.090**</td>
</tr>
<tr>
<td></td>
<td>(-0.174,-0.023)</td>
<td>(-0.160,-0.009)</td>
<td>(-0.164,-0.016)</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.879***</td>
<td>0.897***</td>
<td>0.895***</td>
</tr>
<tr>
<td></td>
<td>(0.497,1.261)</td>
<td>(0.516,1.278)</td>
<td>(0.513,1.276)</td>
</tr>
<tr>
<td>Male partner age:limiting health</td>
<td>-0.137***</td>
<td>-0.141***</td>
<td>-0.130***</td>
</tr>
<tr>
<td></td>
<td>(-0.217,-0.058)</td>
<td>(-0.219,-0.063)</td>
<td>(-0.208,-0.052)</td>
</tr>
<tr>
<td>Household pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>-0.601**</td>
<td>-1.144,-0.058</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.44,-0.69)</td>
<td>(-0.822,0.289)</td>
<td></td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>-0.721***</td>
<td>-1.247,-0.194</td>
<td>-0.565**</td>
</tr>
<tr>
<td></td>
<td>(-1.041,-0.088)</td>
<td>(-0.52,0.331)</td>
<td></td>
</tr>
<tr>
<td>Middle quintile</td>
<td>-0.258</td>
<td>-0.670,0.154</td>
<td></td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household non pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>-0.267</td>
<td>-0.822,0.289</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.342,0.558)</td>
<td>(-0.32,0.289)</td>
<td></td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>-0.110</td>
<td>-0.599**</td>
<td>-1.081,-0.118</td>
</tr>
<tr>
<td></td>
<td>(-0.552,0.331)</td>
<td>(-1.081,-0.118)</td>
<td></td>
</tr>
<tr>
<td>Tenure (ref: owns home outright)</td>
<td>-2.963***</td>
<td>-3.305***</td>
<td>-3.197***</td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.839,-2.087)</td>
<td>(-4.215,-2.394)</td>
<td>(-4.056,-2.339)</td>
</tr>
<tr>
<td>Rent</td>
<td>-0.424***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.732,-0.116)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.413</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.163,0.338)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,701</td>
<td>4,701</td>
<td>4,701</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-696.816</td>
<td>-696.353</td>
<td>-697.860</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>1,427.632</td>
<td>1,426.705</td>
<td>1,425.721</td>
</tr>
</tbody>
</table>

*Note:* *p<0.1; **p<0.05; ***p<0.01
predicted hazard with an estimated probability of exit that is 45.1% lower than for men in
the wealthiest quintile.

With regards to tenure, and sample statistics showed a higher incidence of transitions
amongst men residing in homes that are owned outright with lower rates occurring in those
living in rental properties or with an outstanding mortgage. Results given in Table 5.8,
Model 3 confirm that housing status is a significant predictor of the male partner’s transition
($\chi^2(2) = 7.4193, p = 0.02449$). Those in homes owned outright form the reference category
for this group, and the probability of leaving work associated with having a mortgage is
34.6% lower than it is for the home owners. The reduction in risk for men in rental properties
is similar at 33.8%.

5.4.4 Female partner health

The model containing the three household level variables is adjusted for the income and
health status of the female spouse. Results are given in Table 5.9, Model 1 on page 201.
The result for the health covariate suggests the presence of a limiting condition in the female
member of the household is not a statistically significant predictor of the male partner’s
transition out of work ($\chi^2(1) = 0.2061, p = 0.6498$). This supports the initial findings from
descriptive analysis, that male partners are no more or less likely to leave work if their female
partner has a limiting health condition.

The final model for predicting a transition out of work for the male partners in the studied
households is given in Table 5.9, Model 2. This includes men’s limiting health, household
pension wealth and tenure as statistically significant predictors. A limiting health condition
and high levels of accrued pension wealth raise the risk of transition whereas an outstanding
mortgage or renting are associated with continued employment. In the next section these
results are compared with those from the analysis of women’s transitions that was presented
in Chapter 3.
Table 5.9: Parameter estimates from discrete time event history models for the conditional probability of male partner transitions from employment, with female partner covariates

<table>
<thead>
<tr>
<th></th>
<th>Women’s health and income</th>
<th>Final model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Female partner’s age</td>
<td>−0.033</td>
<td>−0.034</td>
</tr>
<tr>
<td></td>
<td>(-0.099, 0.033)</td>
<td>(-0.100, 0.032)</td>
</tr>
<tr>
<td>Male partner’s age (mean centred)</td>
<td>0.219***</td>
<td>0.221***</td>
</tr>
<tr>
<td></td>
<td>(0.168, 0.270)</td>
<td>(0.170, 0.272)</td>
</tr>
<tr>
<td>Male partner’s income (log)</td>
<td>0.013</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(-0.100, 0.127)</td>
<td>(-0.108, 0.110)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>−0.005</td>
<td>−0.011</td>
</tr>
<tr>
<td></td>
<td>(-0.413, 0.403)</td>
<td>(-0.419, 0.397)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>−0.126</td>
<td>−0.141</td>
</tr>
<tr>
<td></td>
<td>(-0.551, 0.298)</td>
<td>(-0.565, 0.283)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>−0.766***</td>
<td>−0.778***</td>
</tr>
<tr>
<td></td>
<td>(-1.258, -0.275)</td>
<td>(-1.270, -0.287)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>−0.278</td>
<td>−0.286</td>
</tr>
<tr>
<td></td>
<td>(-0.665, 0.110)</td>
<td>(-0.673, 0.100)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>−0.007</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(-0.384, 0.370)</td>
<td>(-0.372, 0.379)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>0.724***</td>
<td>0.712***</td>
</tr>
<tr>
<td></td>
<td>(0.278, 1.170)</td>
<td>(0.266, 1.159)</td>
</tr>
<tr>
<td>Male partner age: part time</td>
<td>−0.090***</td>
<td>−0.090***</td>
</tr>
<tr>
<td></td>
<td>(-0.166, -0.014)</td>
<td>(-0.166, -0.014)</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.917***</td>
<td>0.912***</td>
</tr>
<tr>
<td></td>
<td>(0.534, 1.301)</td>
<td>(0.528, 1.295)</td>
</tr>
<tr>
<td>Male partner age: limiting health</td>
<td>−0.134***</td>
<td>−0.137***</td>
</tr>
<tr>
<td></td>
<td>(-0.212, -0.055)</td>
<td>(-0.215, -0.059)</td>
</tr>
<tr>
<td>Household pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>−0.753***</td>
<td>−0.732***</td>
</tr>
<tr>
<td></td>
<td>(-1.314, -0.192)</td>
<td>(-1.289, -0.176)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>−0.798***</td>
<td>−0.786***</td>
</tr>
<tr>
<td></td>
<td>(-1.338, -0.259)</td>
<td>(-1.324, -0.247)</td>
</tr>
<tr>
<td>Middle quintile</td>
<td>−0.596***</td>
<td>−0.594***</td>
</tr>
<tr>
<td></td>
<td>(-1.081, -0.0110)</td>
<td>(-1.079, -0.0109)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>−0.310</td>
<td>−0.309</td>
</tr>
<tr>
<td></td>
<td>(-0.729, 0.109)</td>
<td>(-0.728, 0.110)</td>
</tr>
<tr>
<td>Household non pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>−0.056</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(-0.668, 0.555)</td>
<td>(-0.683, 0.538)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>0.289</td>
<td>0.281</td>
</tr>
<tr>
<td></td>
<td>(-0.172, 0.750)</td>
<td>(-0.179, 0.741)</td>
</tr>
<tr>
<td>Middle quintile</td>
<td>−0.031</td>
<td>−0.031</td>
</tr>
<tr>
<td></td>
<td>(-0.478, 0.415)</td>
<td>(-0.477, 0.416)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>−0.508***</td>
<td>−0.571***</td>
</tr>
<tr>
<td></td>
<td>(-1.054, -0.081)</td>
<td>(-1.057, -0.084)</td>
</tr>
<tr>
<td>Tenure (ref: owns home outright)</td>
<td>−0.436***</td>
<td>−0.436***</td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>(-0.745, -0.126)</td>
<td>(-0.746, -0.127)</td>
</tr>
<tr>
<td>Rents</td>
<td>−0.028</td>
<td>−0.277</td>
</tr>
<tr>
<td></td>
<td>(-1.123, 0.561)</td>
<td>(-1.121, 0.567)</td>
</tr>
<tr>
<td>Female partner’s income (log)</td>
<td>−0.043</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>(-0.139, 0.052)</td>
<td>(-0.139, 0.052)</td>
</tr>
<tr>
<td>Female partner has limiting health condition</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>−2.422***</td>
<td>−2.574***</td>
</tr>
<tr>
<td></td>
<td>(-3.413, -1.431)</td>
<td>(-3.516, -1.633)</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Observations 4,701 4,701
Log Likelihood -686.596 -687.049
Akaike Inf. Crit. 1,423.192 1,420.098
5.5 Random effect model

The inclusion of a random effect in the event history model for women’s transitions was explained in Chapter 3, Section 3.8. There, a random intercept term was added to account for time invariant unobserved heterogeneity. A random intercept term, \( u_i \sim \mathcal{N}(0, \sigma^2_\mu) \), is incorporated to the model for male partner transitions. However, a hypothesis test with null of \( \sigma^2_\mu = 0 \) against an alternative of \( \sigma^2_\mu > 0 \) returns a statistically insignificant result (\( \chi^2(1) = 0.2061, p = 0.2014 \)). This indicates that there is insufficient between-person variability to justify the inclusion of the random effect and the single level model is sufficient.

5.6 A comparison of women’s and male partner predictors of employment transitions

The focus of this thesis is older women’s transitions out of employment and the role of the domestic context in predicting these. The first research question asks whether labour market exit of women in the United Kingdom is influenced by the household context, with a particular focus on partner characteristics and family financial resources. A series of discrete time event history models were fitted to ELSA data and, as a result of this process, the significant predictors of older women’s transitions were established. These were fully explained in Chapter 3. Limiting health and poor self-rated health, part-time working patterns and having caring responsibilities are all influential for older women’s employment exit. No evidence was found to support the hypotheses that partner health or household pension wealth are also relevant.

In this chapter we have considered in more detail the domestic context in which older women’s employment trajectories unfold by modelling the working patterns of their male partners and spouses throughout the same time period. Event history models were again used, this time to determine whether the factors that influence an older woman’s employment also affect her partner’s chances of continued work. This addressed the third research question which relates to partner health and the impact that it has on the other spouse’s continued employment.
In this section the results for both women’s and partner models are considered together. Table 5.10 summarizes the findings for each. Entries give the estimated impact on the hazard for significant predictors or, alternatively, indicate factors that are either not significant or not tested. Entries are organised according to measurement level with individual level predictors listed first. A more detailed consideration of results relating to the limiting health, part time working and pension wealth variables is given below. In each case a risk profile is constructed for each of an ‘average’ female and male partner that show the predicted probability of a transition occurring during the ten year period prior to the older woman’s state pension age; that is, whilst the female member is aged between 50 and 60. Other covariate values are held at modal or median values.

**Limiting health**

Limiting health is a significant predictor of employment exit for both 50 to 59 year old women and their partners; however the impact of having a such a condition differs for each. The probability of transitioning is an estimated $25.6\%$ higher for women with a limiting illness and this is constant between the ages of 50 and 59. Male partners with health limitations, however, have an estimated risk that is $149\%$ higher with a downwards adjustment of $12.8\%$ for each additional year of age.

Risk trajectories for each of women and male partners according to limiting health status are shown in Figure 5.2. The predicted conditional probability of employment exit is plotted for a ten year period prior to the state pension age, of 60 for women and 65 for men. Solid lines show the predicted hazard for a person in consistently good health with no limiting condition. Dashed lines plot estimates for those who do have a limiting condition in each year within the given age range. In each instance limiting health is the only factor which changes; all other covariates are held at modal or median values.

The vertical distance between each set of solid and dashed lines in Figure 5.2 reflects the differing impact of having a limiting health condition for women compared to their partners. Women with limiting health conditions have a higher predicted conditional probability of leaving work than their peers who are in good health, and this risk differential increases as women approach state pension age. This effect is not observed within the male partner.
Table 5.10: Estimated percentage increase in women’s and male partners’ estimated conditional probability of transition, for selected covariates

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Percentage increase in hazard</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Woman</td>
</tr>
<tr>
<td>Limiting health (main effect)</td>
<td>25.6</td>
</tr>
<tr>
<td>Limiting health (age interaction)</td>
<td>Not sig</td>
</tr>
<tr>
<td>Poor self rated health</td>
<td>74.4</td>
</tr>
<tr>
<td>Caring</td>
<td>62.6</td>
</tr>
<tr>
<td>Part time (main effect)</td>
<td>382</td>
</tr>
<tr>
<td>Part time (age interaction)</td>
<td>-16.8</td>
</tr>
<tr>
<td>Pension wealth quintile</td>
<td></td>
</tr>
<tr>
<td>Poorest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Second poorest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Middle</td>
<td>Not sig</td>
</tr>
<tr>
<td>Second wealthiest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Wealthiest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Non pension wealth quintile</td>
<td></td>
</tr>
<tr>
<td>Poorest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Second poorest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Middle</td>
<td>Not sig</td>
</tr>
<tr>
<td>Second wealthiest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Wealthiest</td>
<td>Not sig</td>
</tr>
<tr>
<td>Tenure</td>
<td></td>
</tr>
<tr>
<td>Own outright</td>
<td>0</td>
</tr>
<tr>
<td>Mortgage</td>
<td>-31.2</td>
</tr>
<tr>
<td>Rent</td>
<td>-16.8</td>
</tr>
<tr>
<td>Partner’s limiting health</td>
<td>Not sig</td>
</tr>
<tr>
<td>Partner’s employment status</td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>0</td>
</tr>
<tr>
<td>Retired</td>
<td>57.8</td>
</tr>
<tr>
<td>Other inactive</td>
<td>18.5</td>
</tr>
</tbody>
</table>
predictions, however. The impact of a limiting condition on male partner transition risk diminishes, rather than increases, over time.

**Part time working**

Working part time is associated with higher risk of employment exit for both older women and their partners. There are, however, differences in the magnitude of the effect between the two populations. The estimated increase in hazard for part time workers compared to full time employees for each group is given in Table 5.10. The effect of part time working
amongst older women raises their risk of exit by 382%, but this is decreased by 16.8% for each additional year of age between 50 and 59. Part time working does raise the risk of leaving work amongst male partners, but to a much lesser extent; the effect for men is estimated at 104% with an downwards adjustment of 8.6% per year.

These results are illustrated graphically in Figure 5.3. In each subfigure solid lines depict a hypothesised trajectory for an average woman or male partner who works full time and the dashed line represents the pathway for a person with the same characteristics, but who is employed part time. The difference in the trajectories between the women and their partners

Figure 5.3: Part time working trajectories for women and male partners
is seen in the vertical distance between the solid and dashed lines; clearly part time working is associated with much greater heterogeneity in risk amongst coupled women than it is within their spouses. This is particularly the case for the oldest of women where the difference in hazard between part time and full time employees is greatest.

**Pension wealth**

Results for the pension wealth covariate from the women’s and partner models are summarized in Table 5.10. This indicator is not a statistically significant predictor of older women’s transitions. The probability that an older woman leaves work does not change with the level of pension wealth accumulated by the couple; women from the poorest of households have the same estimated hazard as those in the wealthiest. This is not the case, however, for the male partners in the studied households. Pension wealth is a significant predictor of male spouse’s exit and there is a positive association between household level of pension resources and the probability of the male partner transitioning. Men in the poorest of households have an estimated hazard that is 51.9% lower than spouses from the wealthiest of couples and that for middle wealth holders is 44.8% less. Pension wealth does, therefore, differentiate between the partners of the women studied here, but not amongst the women themselves.

Figure 5.4 illustrates graphically the heterogeneity in male partner risk associated with pension wealth. This graph plots the predicted conditional probability of male partner transition from employment for the ten years prior to the state pension age of 65. Predictions are calculated from the final partner model using median or modal values of observed measures; the only source of difference between these trajectories is from pension wealth. The highest line represents the pathway for a man in the wealthiest pension group whilst the solid line is that for an average male partner from a couple with the lowest pension resources. Those for middle quintile groups are as indicated in the legend. The noteworthy feature here is that partners from households with the highest level of accumulated pension wealth have a predicted conditional transition probability that is approximately twice that of their poorer counterparts. Women in these households, however, would both have the same level of predicted risk.
5.7 Summary

The primary aim of this chapter was to assess evidence for the asymmetric effect of partner health on transitions from employment. Formally, the third research hypothesis states that partner health has a greater impact on the probability of an older woman leaving work than it does on the transition probability of the male spouse. In Chapter 3 we found no statistically significant evidence that the health status of the male spouse determines the timing of an older woman’s labour force exit. This result was explained by two conflicting theories; the first that in the advent of poor partner health an older woman would be more likely to leave work to provide care. The second explanation, however, is that the woman may continue to work to ensure the economic wellbeing of the family. These two opposing scenarios preclude any statistically significant effect of male partner health on women’s continued employment. In this chapter results indicate that health of the female partner is not a significant predictor of the male partner’s exit. As indicated in the available women’s retirement literature, in the absence of any own personal health issue it is the male spouse that tends to provide the main form of financial support for the couple (Szinovacz and Deviney, 2000). This responsibility may lessen the likelihood that he leaves work to care for the female spouse in the advent of her poor health.

Whilst no statistically significant evidence has been found of a cross spousal effect of
partner health, there is a gender difference in the effect of limiting health on a person’s own transition probability. An older woman with a limiting health condition has an estimated 25.6% higher risk of leaving work compared to a woman with no such limitation. The effect for her male partner, however, is calculated at 149% with an additional 12.8% decrease per year of age. This difference in risk associated with limiting health may reflect men’s greater dependence on disability insurance as a source of replacement income. Eligibility for disability insurance is dependent upon sufficient contributions, but women tend to have more fractured work histories and are thus less likely to meet the set criteria. Men, therefore, make up a greater proportion of disability claimants (Banks et al., 2011).

The impact of household pension wealth on employment trajectories is clear from the analysis presented in this chapter. The probability that an older woman leaves work is independent of the accrued pension wealth of the couple, as established in Chapter 3, but the same is not found for the male partners of these women. A negative linear relationship is established with spouses from the poorest of households predicted the lowest risk of exit. Male partners in the wealthiest of couples, in contrast, are those with the highest chance of exit.

Of the limiting health and wealth covariates examined in this chapter it is health that has the greatest impact on the male spouse’s transition probability with pension resources secondary to this. Amongst working women aged 50 - 59, therefore, it is health that is the most likely predictor of their spouse’s transition from employment with joint pension wealth also influential, although to a lesser extent. Two different household types may emerge from this - both containing working women, but one partnered to a man in poor health and the other with a high level of pension resources. The findings of this chapter, as summarised here, are explained in more depth and with further reference to relevant literature in Chapter 7.
Chapter 6

Sensitivity analysis

6.1 Introduction

Current UK research into older women’s employment is limited to qualitative studies with some contextual information from the analysis of cross sectional data (Loretto and Vickersstaff, 2013; Duberley et al., 2014). This thesis uses longitudinal methods in which women’s later life employment patterns are examined over ten years using repeated observations. This approach involves setting a measurement axis for time, as first raised in the methods description of Chapter 2. The options of age, calendar year or time on study were discussed and an age axis with yearly intervals was considered the most appropriate. However this decision does have consequences for the incidence and influence of missing data in the analysis. Dong and Peng (2013) summarize the impact that missing data can have on research; it can result in biased parameter estimates and weaken generalizability of results, and failure to include cases with unknown values is a loss of information with consequential decrease in statistical power and increased standard errors. In this chapter we focus on the patterns, causes and implications of missing data in the ELSA sample used for the modelling of women’s employment transitions detailed in Chapter 3. Methods for addressing these issues are also discussed.

Prior to the deletion of records with missing covariate values there were 2238 working women aged between 50 and 59 in the selected sample, as described in Section 2.2.1. The majority of these women did not enter ELSA at the age of 50 nor remain in until 59, and questionnaires were not distributed on a yearly basis. Consequently observation rates differ
for each year of age within this time frame. Figure 6.1 shows the proportion of the sample of 2238 women who responded by year of age. The bar plotted at age 50, for example, indicates that 15% of these 2238 women were interviewed at this age, whereas the second bar shows twenty one percent responded at age 51. It is at these earlier ages that the greatest proportion of missing data occurs. The lowest incidence of missingness is between the ages of 56 and 58 with the percentage of women without measurements for these years ranging between 61% and 63%.

The rates of missingness plotted in Figure 6.1 provide a summary measure for each time point. Figure 6.2 gives a more comprehensive picture of the pattern of missing data in the sample as it depicts sequences of unknown and observed values over time. The horizontal axis of this plot marks each year of age between 50 and 59 and sequences are read from left to right. White regions denote ages at which women have not been observed and black and grey areas indicate ages where data has been recorded. The vertical axis gives the cumulative percentage of the 2238 sampled women that follow the given patterns. The most common observation sequence has women with measurements taken at ages 56 and 58, but missing for
every other year; there are 154 women with this sequence and this is 6.9% of the sample. The next most frequent pattern has 126 women with observations at 54, 56 and 58, but missing elsewhere; this group form 5.6% of the sample. Following this it is women responding at ages 55, 57 and 59 and 53, 55, 57 and 59 that occur in 5.5% and 5.0% of the sample respectively.

Figure 6.2: Women’s observation patterns according to age

Figure 6.2 is useful for showing how the biennial design of ELSA study results in missing data when employment trajectories are constructed along a yearly age axis. Two yearly response patterns cause the alternating coloured/white patterns of known values and missingness, and regions of white at the beginning of a sequence denote unobserved periods due to women entering ELSA at older ages rather than 50. This delayed entry also causes sequences to be out of alignment with each other in that some women are observed at ‘even’ ages (black) and others at ‘odd’ (grey). White regions at the right end of sequences indicate unobserved periods that occur when women’s observation windows close prior to age 59.
The event history models used in this research were fitted to complete case only data; alternative methods to deletion are considered in Sections 6.2 and 6.3. Section 6.4 concludes.

6.2 Imputation of missing values

In this section imputation methods for unknown employment states are considered; single imputation is covered in Section 6.2.1 and multiple imputation in Section 6.2.2.

6.2.1 Single imputation of employment status in non-observed periods

The event history models used in this research are fitted in a conditional likelihood framework, in which it is assumed that women are in continuous employment from the age of 50 until either the age of censorship or first observed transition. However, as was first raised in Chapter 1, evidence from the available literature on women’s retirement trajectories suggests that older women have more erratic working patterns with periods of non-employment alternating with work (Loretto and Vickerstaff, 2013). The aim of this section is to investigate an alternative approach to conditional likelihood.

The method undertaken here involves imputing the employment status for periods where women were not observed. We work with the data on a cross sectional basis and consider separately subgroups of the sample defined by year of age. A two-step imputation process is followed for each group. Firstly, a logistic regression model is fitted for calculating the probability that a period of non-employment - that is, either retirement, illness, unemployment or caring - occurs. This is formally stated in Equation 6.1.

\[
\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1i} + ... + \beta_p x_{pi}
\] (6.1)

The outcome is the transformed probability of non-employment, \( p_i = Pr[Y_i = 1] \) for individual \( i \), and this is estimated from observations on the available cases. However not all measures from the available cases are used to fit this model. Rather, predictors are restricted to the time invariant characteristics of social class, education, tenure and dependent children. This choice of covariates arises from the requirements of the second step in the imputation process. If the outcome \( Y_i \) is missing for a given observation then \( p_i \) is estimated from the
fitted model and we impute $Y_i = 1$ if $\hat{p}_i > 0.5$ and $Y_i = 0$ otherwise. However where observations are missing the outcome, they are also missing values for the time varying covariates. Consequently the above time invariant measures are the only indicators available for calculating the estimates of $p_i$ in this second stage.

Following this procedure, respondents have an indicator of labour market status at ages that were previously denoted as missing. However the number of periods of non-employment in the new imputed outcome measure did not change - in all instances the imputed outcomes took value 0, indicating that no new events appeared in the dataset and there remained 287 recorded transitions. The number of periods in which no transition is recorded did, however, significantly increase. Whilst previously there were 5895 person period records indicating no transition this increased to 9937 such periods, and consequently the sample transition rate fell from 4.6% to 2.8%.

Of interest now is the rate of event occurrence over time and how this has changed with the imputed outcomes. Table 6.1 shows the transition rate for each year of age - in the first row, for the dataset that contains observed outcomes only and in the second, transition rates for the larger dataset containing imputed outcomes. Both sets of data are plotted in Figure 6.3. The imputation process has had a greater impact on transition rates for women at younger ages; the difference between the two rates is greater for women in their early fifties with 3.3% of 51 year old women having recorded transitions in the original dataset, but only 1.1% of them doing so when imputed records are also taken into account. By the end of the studied age range, however, the two transition rates have converged to 9%.

Table 6.1: Transition rate for each age group with and without imputed outcomes (%)

<table>
<thead>
<tr>
<th>Age</th>
<th>Records in dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>51</td>
</tr>
<tr>
<td>Observed outcomes only</td>
<td>3.3</td>
</tr>
<tr>
<td>With imputed outcomes</td>
<td>1.1</td>
</tr>
</tbody>
</table>

From the above, it is clear that the majority of imputed records are allocated to women of younger ages. This is as expected for a truncated sample. The imputation process implemented here has addressed the missingness that occurs both due to delayed entry that occurs at the beginning of employment sequences as well as that which persists within the
observation window. Because of the delayed entry issue, however, a significant number of the new imputed records denoting no transition have been created for women in their early fifties. Transition rates for women at these younger years have therefore decreased by more than those for older women.

6.2.2 Multiple imputation of employment status in non-observed periods

In the previous section we described the implementation and results of a single imputation method for women’s employment status in non-observed periods. However that method does not account for any uncertainty in the value of the imputed measure; rather, just one predicted probability of labour market status is generated. Additionally this method focuses only on unknown outcomes. Missingness in covariate measures are not addressed and consequently, only observed time invariant characteristics are used to impute any unknown employment status. In this next stage of analysis the application of multiple imputation methods are considered, in which both unobserved outcomes and predictor values are estimated. This process does account for uncertainty in the true value of the studied measures as multiple estimates for each unknown are generated; uncertainty enters through the difference between these estimates. In the next section the imputation process as applied to the ELSA sample
is described. We briefly present the method, challenges faced, ensuing results and their limitations.

6.2.2.1 The application of MICE to ELSA

The final model for coupled women’s transitions, as presented in Chapter 3, was a random intercept event history model, with a binary outcome measure for predicting the change in a woman’s labour market status from employment to a non-employed state. The model included individual level control factors of education, social class and income as well as the significant predictors of working hours, health and caring. The household measure of tenure was also retained as were indicators of partner’s age, income and employment status. Education, social class and tenure were entered as time invariant measures, but other predictors are time varying in that the value of each could change across time points. The aim here is to generate multiple estimates for both the missing outcome and missing observations of the time varying covariates from this final model.

The Multiple Imputation of Chained Equations (MICE) procedure from Van Buuren and Oudshoorn (2000) is implemented to achieve the above. The MICE method imputes both unobserved outcomes and covariate values; however the transition indicator is not directly imputed. Rather, complete sequences of the underlying employment states are generated and a transition indicator is constructed from these. The MICE process will generate values for a given measure at any given time point without adjusting for the status of that measure at earlier or later times. Consequently, if the transition indicator was imputed directly it is possible that a sequence of transitions could be generated at consecutive ages. Given the definition of transition used in this analysis - that is, a change in status from employed to not on two consecutive occasions - it is only possible for transitions to be recorded with a minimum of two years in between. To avoid this situation we instead work with employment states, and will later re-evaluate the timing and occurrence of any transitions in this new dataset compared to those observed in the complete cases version.

Two issues pertinent to estimating any unknown covariate values in a longitudinal study are the structure of the dataset and particular patterns of missingness. When in wide format, the ELSA data in this study is comprised of one row for each woman, time invariant
characteristics are recorded in singular columns, and each time varying covariate has one column per year of age. The same data in person-period form consists of multiple rows per woman with each individual record containing measurements of covariates for a specific age. Van Buuren (2012) discusses multiple imputation methods for longitudinal data presented in each of these forms. Working with the wide form structure is the more straightforward approach if missingness occurs systematically, in regular patterns; it is not the recommended or most viable option where it has a more irregular, unpredictable arrangement. This option of imputing in wide form was investigated in detail for this research, and was indeed problematic. When the MICE process was applied to our ELSA sample it failed to fully impute several covariate measures. Missingness was still present in health and partner variables.

One possible explanation for this persistent missingness relates to the modelling of retirement along a yearly age axis. A complete set of covariate measurements for any given woman in the ELSA sample would consist of one value for each year of age between 50 and 59. Now, Van Buuren and Oudshoorn (2000) recommend that the imputation model used in the MICE algorithm contains all predictors from the corresponding complete case analysis. In this case that is the set of individual, household and partner covariates from the final model for the coupled women’s transitions mentioned above. However many of these variables, including health, caring and pension wealth quintiles, are entered as time varying measures and as such, each requires nine separate indicators in the wide form dataset. This clearly leads to a large number of predictors in the imputation model. Additionally, as explained in the introduction to this chapter, at each year of age there is a high proportion of unobserved women. Consequently there is limited information on each predictor from which missing values can be imputed. Structuring time along a yearly age axis has therefore led to a large number of predictors and reasonably scarce distribution of known values across these predictors. The MICE process is consequently inappropriate for imputing the wide format ELSA data.

The alternative option is to address missingness with the dataset configured in person-period form. In this format respondents have multiple records, and each contains measurements relating to one year of age. However imputation in this structure requires multilevel methods for imputing binary outcomes, which is a lengthy and complex procedure requiring
time and computing resources that are unavailable for this research.

6.2.2.2 Alternative multiple imputation methods

The MICE approach detailed in the previous section does not take into account temporal ordering of observations in longitudinal data. Equal weight is placed on measurements irrespective of their position on the time axis. Welch et al. (2014) detail the two-fold conditional specification multiple imputation algorithm which conditions on near observations. The gain from this approach depends on the strength of correlation both within and between variables; the extent to which, for example, employment is correlated with past and future employment status compared to health or wealth. As with the MICE approach, the two-fold conditional specification is sensitive to the scale of the time axis, because this determines the distribution of events and known measurements in the nearby intervals from which unobserved measurements are imputed. The inclusion of delayed entry participants in the ELSA sample studied in this thesis would force the construction of narrow time intervals due to their shortened observation windows. Also, there would be limited gain in predicting employment states using past or future values as only working women are observed. There is therefore insufficient heterogeneity in labour market states to inform imputation.

Amelia II is an R software programme for the imputation of missing data (Honaker et al., 2011). It uses an expectation-maximisation algorithm on multiple bootstrapped samples to generate imputed values. Schafer and Yucel (2002) present a multiple imputation strategy that is also based on the expectation-maximisation algorithm, as well an alternative involving Markov chain Monte Carlo methods. However both of these, as well as the Amelia approach, assume that observed and unobserved data follow a multivariate normal distribution. This is problematic in the context of this retirement research, because the majority of measurements in the selected ELSA sample are binary or categorical. There are methods by which values may be imputed as multivariate normal and subsequently converted to binary measures (Bernaards et al., 2007), but Schafer and Yucel (2002) assert these provide only approximate solutions and, consequently, a detailed sensitivity analysis of parameter estimates to these methods would be required should they be adopted for future work involving multiple imputation of binary measures.
Raghunathan et al. (2001) detail a multiple imputation technique that allows for a variety of covariate structures, including binary, categorical and continuous. The sequential regression multivariate imputation method involves fitting a series of regression models that vary according to the structure of the imputed variable, using IVEware software. This approach does not, however, make any particular allowance for complex survey structures and longitudinal data. It is therefore unlikely to offer any advantage over other multiple imputation methods discussed here, if applied to the ELSA sample analysed in this research.

6.3 Minimising missingness: alternative sample selection and time structures

Earlier sections of this chapter detailed the incidence of missing data in the ELSA sample analysed for this research. Modelling retirement trajectories along an age axis, with women observed from different starting points, caused missingness at the beginning of employment sequences; this was dealt with using a conditional likelihood modelling approach in which it was assumed that the first transition observed was the first which occurred. Additionally, using yearly age units contributes to missingness within women’s observation windows. Single and multiple imputation methods for addressing missingness were considered in Sections 6.2.1 and 6.2.2 respectively. However neither imputation approach was satisfactory for these circumstances. Single imputation does not account for uncertainty within the unknown values, but multiple imputation techniques failed to produce estimates for a number of unknown covariate measures. Given these limitations, alternative approaches are detailed here. These involve reconfiguring the time axis along which women’s employment trajectories are positioned, and the exclusion of delayed entry cases. In the first instance a compressed interval age axis is considered and following that, the options and implications of using the alternative time metric of time on study are discussed.

6.3.1 Interval baseline hazard functions

This research analysed women’s employment trajectories in the ten years prior to their state pension age of 60. However few women in the selected ELSA sample were observed from
the starting age of 50 and additionally, all had at least a two year gap between questionnaires. This sampling scheme lead to some members having observations on some or all of the ‘even’ ages of 50, 52, 54, 56 or 58, whilst others are recorded on some or all of the alternative ‘odd’ years. A third group of women have neither of these response patterns and instead follow a variety of alternatives. A particular challenge of modelling trajectories in these circumstances is the way in which the three subgroups are integrated and positioned along one common time axis. In this analysis a one yearly scale was used, in which women of the same age are compared. Alternatively a compressed age axis could be formed from combining women of consecutive ages into intervals of two years; in this structure women aged 50 and 51 would be pooled together as would women aged 52 and 53 and so on, with 58 and 59 year old women forming the oldest group. The fitted event history models would be consequently constructed from of a piecewise baseline hazard function estimated on five measurement points rather than ten. Interval baseline hazard functions are seen elsewhere in couple’s retirement research; Drobnič (2002) is one example. In that work an age specific baseline hazard function is fitted with persons aged 50 and over grouped into six intervals of unequal width.

Fitting a piecewise baseline hazard in the manner described here would minimise the incidence of unknown values within the observation window, but results in the loss of detail surrounding older women’s employment trajectories. Fewer time points are used in the baseline function and estimated effect sizes and hazards are predicted for each interval rather than year of age. However there is a counterargument to this, in that the knowledge gained from using a one yearly scale depends upon assumptions pertaining to unobserved employment states and covariate values. In some circumstances a less detailed analysis based on known and observed data rather than more detailed results contingent on the analyst’s assumptions may be preferable.

Whilst a piecewise hazard minimises missingness within the observation window, it does not address that caused by the delayed entry of some respondents. Missing values at the beginning of the time axis arise when sample members have an observation window that begins later than the starting point of the chosen axis. Compressing the age axis scale does not change when respondents’ observation windows begin; it only lowers the number of time
points that are placed after entry. Consequently missingness at the beginning of the observed sequences would persist and modelling of transitions using event history methods would still need to be done under a conditional likelihood approach. In the next two sections we consider alternative options for analysing ELSA data longitudinally that resolve the delayed entry issue as well as minimise missingness within the observation window. The first is to combine an interval axis on a more tightly defined sample that does not include delayed entry cases. The second approach, presented in Section 6.3.3, involves structuring observations along a time on study, rather than age axis.

### 6.3.2 Interval baseline hazard with no delayed entry cases

The women selected for the analysis of transitions presented in Chapter 3 were aged between 50 and 59 on entry to the ELSA study. Selecting women between a range of ages led to a truncated sample, in which some respondents were at risk of leaving work prior to the beginning of their observation window and missing data occurred at the beginning of the affected women’s employment sequences. Additionally, missing data also occurred within observation windows; this was a consequence of positioning measurements along an age axis measured in yearly units. The first of these issues was addressed by modelling under a conditional likelihood framework in which it was assumed that the first transition observed was the first that occurred. Missingness within the observation window was dealt with firstly by using a modified ‘last value carried forward’ approach, and then by the deletion of any records that still contained any unknown values.

This summary of earlier modelling issues highlights two particular methodological decisions for which there are alternative strategies that could be followed. The first concerns the inclusion of partially observed women in the sample, and the second relates to the choice of a yearly age time scale. In this section, we examine the consequence of excluding late entry respondents from the sample as well as using an interval time axis. These changes, made together, negate the reliance on the conditional assumption, minimise the incidence of missing data and result in a more straightforward modelling process. This efficiency would be of particular interest in situations where the conditional assumption may be questionable or where there is limited capacity to deal with complex missing data issues. It may, however,
result in different conclusions with regards to covariates and effect sizes. The aim here is to investigate the effect that conducting a less complex and simpler analysis might have on resulting conclusions; we consider whether the relationship between the variables of interest and women’s transitions that was established in Chapter 3 is replicated in this alternative, less complex approach. This debate is motivated by existing retirement research; Madero-Cabib et al. (2016) is one example of a retirement study of couples that uses such a restricted sample.

In the ELSA dataset analysed for this thesis, sampling only women that are observed from the ages of 50 - 52 and eliminating those that entered later decreased the number of studied cases from 1569 to 771. The number of transitions observed falls from 287 to 150. The employment data of women in this restricted sample is positioned along an age axis structured in a combination of four two or three year intervals; it is not necessary for intervals to be of equal width (Singer and Willett, 2003). Women of ages 51 and 52 are grouped together, as are those aged 53 and 54, 55 and 56, and 57, 58 and 59. This grouping effectively forms a categorical variable for age with the youngest forming the baseline category. The resulting discrete time event history models will, therefore, contain a baseline hazard function fitted to four time points. In this structure missing data within a woman’s observation window is limited to non-response, because any missingness arising from the use of a one yearly age scale is eliminated; this effectively removes the ‘evens’ and ‘odds’ patterns of observation caused by the biennial design of ELSA, as described in the introduction to this chapter. As a consequence of adopting this four point time axis, in the person-period data set respondents have between one and four records each; previously, in the original sample, this was up to nine records representing ages 51 - 59. The overall effect of these changes to the observed transition rate in the person-period data sets is an increase from 4.6% in the original sample of 1569 women, to 8.0% for the 771 women who entered between the ages of 50 and 52.

The discrete time event history models for women’s transitions formally specified in the methods section of Chapter 2 are fitted to this smaller sample of 771 women. Of particular interest is whether the significance and estimated effects of covariates change from that which was established in Chapter 3, when all women aged between 50 - 59 were analysed.
under a conditional likelihood framework. A similar modelling process is followed, in that individual level covariates are fitted first, followed by household and partner level measures. Results for the individual level models are given in Table 6.2, for household models in Table 6.3 and partner versions in Table 6.4.

Table 6.2: Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, for women observed from ages 50 - 52, using interval baseline hazard function with individual level covariates

<table>
<thead>
<tr>
<th>Age group</th>
<th>Limiting health</th>
<th>Self rated</th>
<th>Caring</th>
<th>Part time</th>
</tr>
</thead>
<tbody>
<tr>
<td>(ref: women aged 51/52)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Age 53/54</td>
<td>0.540**</td>
<td>0.530**</td>
<td>0.543**</td>
<td>1.078***</td>
</tr>
<tr>
<td>(0.126,0.954)</td>
<td>(0.116,0.943)</td>
<td>(0.129,0.956)</td>
<td>(0.298,1.857)</td>
<td></td>
</tr>
<tr>
<td>Age 55/56</td>
<td>0.831***</td>
<td>0.834***</td>
<td>0.835***</td>
<td>0.986**</td>
</tr>
<tr>
<td>(0.389,1.272)</td>
<td>(0.392,1.276)</td>
<td>(0.393,1.276)</td>
<td>(0.075,1.897)</td>
<td></td>
</tr>
<tr>
<td>Age 57/58/59</td>
<td>1.342***</td>
<td>1.351***</td>
<td>1.354***</td>
<td>2.290***</td>
</tr>
<tr>
<td>(0.864,1.820)</td>
<td>(0.872,1.829)</td>
<td>(0.876,1.833)</td>
<td>(1.497,3.083)</td>
<td></td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.253</td>
<td>-0.271</td>
<td>-0.266</td>
<td>-0.270</td>
</tr>
<tr>
<td>(0.673,0.167)</td>
<td>(0.691,0.149)</td>
<td>(0.688,0.155)</td>
<td>(0.688,0.148)</td>
<td></td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>-0.169</td>
<td>-0.179</td>
<td>-0.174</td>
<td>-0.199</td>
</tr>
<tr>
<td>(0.663,0.326)</td>
<td>(0.674,0.316)</td>
<td>(0.668,0.320)</td>
<td>(0.693,0.295)</td>
<td></td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.289</td>
<td>0.278</td>
<td>0.282</td>
<td>0.124</td>
</tr>
<tr>
<td>(-0.142,0.719)</td>
<td>(-0.153,0.709)</td>
<td>(-0.148,0.713)</td>
<td>(-0.320,0.568)</td>
<td></td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>0.128</td>
<td>0.080</td>
<td>0.128</td>
<td>-0.089</td>
</tr>
<tr>
<td>(0.355,0.612)</td>
<td>(-0.408,0.568)</td>
<td>(-0.354,0.610)</td>
<td>(-0.587,0.410)</td>
<td></td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.072</td>
<td>-0.071</td>
<td>-0.074</td>
<td>-0.050</td>
</tr>
<tr>
<td>(0.163,0.020)</td>
<td>(0.162,0.020)</td>
<td>(0.166,0.018)</td>
<td>(0.147,0.047)</td>
<td></td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.067</td>
<td>-0.055</td>
<td>-0.058</td>
<td>-0.086</td>
</tr>
<tr>
<td>(0.448,0.314)</td>
<td>(0.436,0.326)</td>
<td>(0.439,0.323)</td>
<td>(0.467,0.294)</td>
<td></td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.119</td>
<td>0.552**</td>
<td>0.298</td>
<td></td>
</tr>
<tr>
<td>(0.321,0.559)</td>
<td>(-0.038,0.106)</td>
<td>(-0.104,0.700)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.552**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>(0.038,0.106)</td>
<td>0.298</td>
<td>(0.135,0.817)</td>
<td></td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 53/54:Part time</td>
<td>-0.787*</td>
<td>-1.710,0.137</td>
<td>-0.239</td>
<td></td>
</tr>
<tr>
<td>Age 55/56: Part time</td>
<td>-0.239</td>
<td>-1.281,0.803</td>
<td>-1.533**</td>
<td></td>
</tr>
<tr>
<td>Age 57/58/59: Part time</td>
<td>-1.533**</td>
<td>(2.558,0.509)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.560***</td>
<td>-2.569***</td>
<td>-2.581***</td>
<td>-3.254***</td>
</tr>
<tr>
<td>(-3.270,-1.850)</td>
<td>(-3.277,-1.861)</td>
<td>(-3.293,-1.870)</td>
<td>(-4.152,-2.357)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,867</td>
<td>1,867</td>
<td>1,867</td>
<td>1,867</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>1,027.520</td>
<td>1,023.906</td>
<td>1,025.810</td>
<td>1,014.442</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
In this sample of 50 - 52 year old women, the relationship between time and the probability of exit is expressed with a piecewise baseline function that compares the hazard for each age interval to that of women aged 51 - 52. The individual level socio demographic factors of education, social class, dependent children and income are then added to this baseline model. Following that the measures of women’s limiting health, self rated health, caring responsibilities and part time working hours are incorporated in turn (Table 6.2, Models 1 - 4). Of these four factors self rated health is statistically significant at the 5% level ($\chi^2(1) = 3.96, p = 0.047$); so also is working part time ($\chi^2(1) = 9.32, p = 0.002$). The effect of part time working hours varies over time, as evidenced by a significant age interaction term ($\chi^2(1) = 5.9961, p = 0.0143$). An indicator for decline in health status was also tested, but not found significant ($\chi^2(1) = 2.046, p = 0.1526$).

The self rated health and part time predictors are retained in the model and the household covariates of tenure, pension wealth and non pension wealth are added to this in turn. Results are given in Table 6.3 on page 226. Tenure is not a statistically significant factor (Model 1, $\chi^2(2) = 2.1014, p = 0.3497$) and neither is pension wealth (Model 2, $\chi^2(4) = 9.1082, p = 0.0584$). There is, however, evidence from this sample that non pension wealth predicts women’s exit (Model 3, $\chi^2(4) = 12.932, p = 0.0116$). The current version of this model therefore contains the individual level control factors as well as indicators for self rated health, part time working and non pension wealth.

The male partner control measures of individual income and age are added to the model containing significant household variables, followed by the particular spousal indicators of interest; namely, employment status and limiting health. Estimated coefficients from these models are in Table 6.4 (page 227). The employment status indicator is not statistically significant (Model 1, $\chi^2(2) = 3.6509, p = 0.1611$), but the health indicator is (Model 2, $\chi^2(1) = 5.8965, p = 0.01517$) and has an estimated coefficient of 0.485. This suggests that, in this model, the probability of a woman leaving work if her partner has a limiting health condition is 62.4% higher than it would be if her partner had no such health problem.

From this sample therefore, that has no delayed entry participants and uses an interval age axis, the significant predictors of women’s labour market exit are poor self rated health, working part time, household non pension wealth and having a partner with a limiting health
condition. Poor self rated health, part time hours and a male spouse with a health limitation each raise the risk of transition, and women in the wealthiest quintile for household non pension wealth have the highest estimated probability of exit. A comparison of these results with those obtained in the original analysis of Chapter 3 is given later, in Section 6.4. Before this, the option of using a time on study rather than age metric is considered.

6.3.3 Time on study axis

Missing data at the beginning, and within, the older women’s employment trajectories studied in this thesis is a result of sampling women with a wide range of entry ages, and positioning their observations along a yearly age axis. The strategy used for addressing the delayed entry issue in Chapter 3 was to model under a conditional likelihood framework in which it was assumed that women were in continual employment between the age of 50 and first entry into ELSA. A modified ‘last value carried forward’ method was used to impute missing values within the observation window, and following that any cases with remaining unknown values were removed from the sample. In the previous section, we detailed how sampling women from a more tightly defined age range of 50 - 52 at baseline and positioning measurements along a compressed interval age axis could minimise the incidence of missingness both at the beginning and within the observation window. This approach is similar to that used in recent studies of families and retirement timing (Madero-Cabib et al., 2016). However there is an alternative option seen elsewhere in the literature; rather than structure the retirement process along an age axis, a ‘time on study’ scale is used (Blau and Riphahn, 1999; Szinovacz et al., 2001). This is advantageous because the wider age range of 50 - 59 on entry is sampled rather than the more restricted option of 50 - 52. However there are implications and consequences of using an alternative time structure, and these are considered in this section.

A time on study metric involves grouping the sampled women - all of whom are aged between 50 and 59 on first entry - according to how long they have participated in ELSA for. All sample members would have an employment trajectory comprised of a series of consecutive labour market states beginning with that recorded in their first observation. In this structure the baseline hazard function is estimated from the number of ELSA interviews
Table 6.3: Parameter estimates from discrete time event history models of the conditional probability of women’s transition from employment, for women observed from ages 50 - 52, using interval baseline hazard function with household level covariates

<table>
<thead>
<tr>
<th></th>
<th>Tenure</th>
<th>Household pension wealth</th>
<th>Household non pension wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age group (ref: women aged 51/52)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 53/54</td>
<td>1.056***</td>
<td>1.080***</td>
<td>1.056***</td>
</tr>
<tr>
<td></td>
<td>(0.277,1.836)</td>
<td>(0.299,1.860)</td>
<td>(0.275,1.836)</td>
</tr>
<tr>
<td>Age 55/56</td>
<td>0.968**</td>
<td>1.028**</td>
<td>0.987**</td>
</tr>
<tr>
<td></td>
<td>(0.057,1.879)</td>
<td>(0.114,1.937)</td>
<td>(0.076,1.899)</td>
</tr>
<tr>
<td>Age 57/58/59</td>
<td>2.320***</td>
<td>2.309***</td>
<td>2.309***</td>
</tr>
<tr>
<td></td>
<td>(1.527,3.113)</td>
<td>(1.515,3.103)</td>
<td>(1.515,3.102)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.285</td>
<td>-0.299</td>
<td>-0.353</td>
</tr>
<tr>
<td></td>
<td>(-0.707,0.136)</td>
<td>(-0.724,0.126)</td>
<td>(-0.775,0.069)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.232</td>
<td>-0.313</td>
<td>-0.361</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.080</td>
<td>0.137</td>
<td>0.136</td>
</tr>
<tr>
<td></td>
<td>(-0.366,0.526)</td>
<td>(-0.314,0.588)</td>
<td>(-0.309,0.582)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.195</td>
<td>-0.079</td>
<td>-0.066</td>
</tr>
<tr>
<td></td>
<td>(-0.705,0.314)</td>
<td>(-0.588,0.429)</td>
<td>(-0.580,0.448)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.043</td>
<td>-0.051</td>
<td>-0.050</td>
</tr>
<tr>
<td></td>
<td>(-0.141,0.055)</td>
<td>(-0.148,0.046)</td>
<td>(-0.145,0.045)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.067</td>
<td>-0.118</td>
<td>-0.152</td>
</tr>
<tr>
<td></td>
<td>(-0.451,0.316)</td>
<td>(-0.500,0.263)</td>
<td>(-0.537,0.233)</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.650**</td>
<td>0.637**</td>
<td>0.667**</td>
</tr>
<tr>
<td></td>
<td>(0.133,1.167)</td>
<td>(0.121,1.154)</td>
<td>(0.149,1.185)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>1.131***</td>
<td>1.147***</td>
<td>1.112***</td>
</tr>
<tr>
<td></td>
<td>(0.448,1.814)</td>
<td>(0.464,1.830)</td>
<td>(0.429,1.794)</td>
</tr>
<tr>
<td>Age 53/54:Part time</td>
<td>-0.764</td>
<td>-0.784*</td>
<td>-0.781*</td>
</tr>
<tr>
<td></td>
<td>(-1.687,0.159)</td>
<td>(-1.708,0.140)</td>
<td>(-1.705,0.143)</td>
</tr>
<tr>
<td>Age 55/56:Part time</td>
<td>-0.202</td>
<td>-0.251</td>
<td>-0.233</td>
</tr>
<tr>
<td></td>
<td>(-1.245,0.842)</td>
<td>(-1.295,0.792)</td>
<td>(-1.266,0.820)</td>
</tr>
<tr>
<td>Age 57/58/59:Part time</td>
<td>-1.529***</td>
<td>-1.552***</td>
<td>-1.535***</td>
</tr>
<tr>
<td></td>
<td>(-2.555,-0.503)</td>
<td>(-2.579,-0.526)</td>
<td>(-2.561,-0.508)</td>
</tr>
<tr>
<td>Tenure (ref: owns home outright)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>-0.259</td>
<td>-0.233</td>
<td>-0.233</td>
</tr>
<tr>
<td></td>
<td>(-0.601,0.083)</td>
<td>(-0.755,0.289)</td>
<td>(-0.755,0.289)</td>
</tr>
<tr>
<td>Rents</td>
<td>-0.107</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.832,0.618)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td></td>
<td>-0.233</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.755,0.289)</td>
<td>(-0.755,0.289)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td></td>
<td>-0.417</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.939,0.105)</td>
<td>(-0.939,0.105)</td>
</tr>
<tr>
<td>Middle quintile</td>
<td></td>
<td>-0.740***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.278,-0.202)</td>
<td>(-1.278,-0.202)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td></td>
<td>-0.488*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.981,0.005)</td>
<td>(-0.981,0.005)</td>
</tr>
<tr>
<td>Household non pension wealth (ref: wealthiest)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td></td>
<td>-0.455</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.029,0.118)</td>
<td>(-1.029,0.118)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td></td>
<td>-0.991***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-1.581,-0.401)</td>
<td>(-1.581,-0.401)</td>
</tr>
<tr>
<td>Middle quintile</td>
<td></td>
<td>-0.219</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.687,0.250)</td>
<td>(-0.687,0.250)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td></td>
<td>-0.276</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.738,0.185)</td>
<td>(-0.738,0.185)</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.127***</td>
<td>-2.917***</td>
<td>-2.871***</td>
</tr>
<tr>
<td></td>
<td>(-4.063,-2.191)</td>
<td>(-3.884,-1.951)</td>
<td>(-3.818,-1.923)</td>
</tr>
<tr>
<td>Observations</td>
<td>1.867</td>
<td>1.867</td>
<td>1.867</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-489.624</td>
<td>-486.240</td>
<td>-484.288</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>1,013.247</td>
<td>1,010.480</td>
<td>1,006.577</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Table 6.4: Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, for women observed from ages 50 - 52, using interval baseline hazard function with male partner level covariates

<table>
<thead>
<tr>
<th></th>
<th>Partner’s employment (1)</th>
<th>Partner’s health (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age group (ref: women aged 51/52)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 53/54</td>
<td>1.056***</td>
<td>1.065***</td>
</tr>
<tr>
<td></td>
<td>(0.272,1.839)</td>
<td>(0.283,1.848)</td>
</tr>
<tr>
<td>Age 55/56</td>
<td>0.962**</td>
<td>0.954**</td>
</tr>
<tr>
<td></td>
<td>(0.037,1.887)</td>
<td>(0.029,1.878)</td>
</tr>
<tr>
<td>Age 57/58/59</td>
<td>2.268***</td>
<td>2.254***</td>
</tr>
<tr>
<td></td>
<td>(1.466,3.109)</td>
<td>(1.432,3.075)</td>
</tr>
<tr>
<td><strong>Education (ref: less than O level)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.367</td>
<td>-0.353</td>
</tr>
<tr>
<td></td>
<td>(-0.792,0.059)</td>
<td>(-0.780,0.073)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>-0.415</td>
<td>-0.391</td>
</tr>
<tr>
<td></td>
<td>(-0.935,0.106)</td>
<td>(-0.908,0.125)</td>
</tr>
<tr>
<td><strong>Social class (ref: managerial/professional)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.106</td>
<td>0.113</td>
</tr>
<tr>
<td></td>
<td>(-0.340,0.552)</td>
<td>(-0.332,0.557)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.104</td>
<td>-0.094</td>
</tr>
<tr>
<td></td>
<td>(-0.621,0.413)</td>
<td>(-0.610,0.423)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.055</td>
<td>-0.058</td>
</tr>
<tr>
<td></td>
<td>(-0.152,0.042)</td>
<td>(-0.155,0.039)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.158</td>
<td>-0.144</td>
</tr>
<tr>
<td></td>
<td>(-0.545,0.228)</td>
<td>(-0.531,0.243)</td>
</tr>
<tr>
<td><strong>Household non pension wealth (ref: wealthiest)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>-0.511</td>
<td>-0.571</td>
</tr>
<tr>
<td></td>
<td>(-1.104,0.082)</td>
<td>(-1.160,0.018)</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>-0.971***</td>
<td>-0.992***</td>
</tr>
<tr>
<td></td>
<td>(-1.568,-0.374)</td>
<td>(-1.584,-0.399)</td>
</tr>
<tr>
<td>Third poorest quintile</td>
<td>-0.202</td>
<td>-0.217</td>
</tr>
<tr>
<td></td>
<td>(-0.672,0.269)</td>
<td>(-0.687,0.252)</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>-0.240</td>
<td>-0.285</td>
</tr>
<tr>
<td></td>
<td>(-0.705,0.226)</td>
<td>(-0.748,0.178)</td>
</tr>
<tr>
<td>Partner’s income (log)</td>
<td>0.041</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td>(-0.059,0.140)</td>
<td>(-0.067,0.125)</td>
</tr>
<tr>
<td>Partner’s age</td>
<td>-0.003</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(-0.041,0.034)</td>
<td>(-0.034,0.035)</td>
</tr>
<tr>
<td><strong>Partner employment status (ref: employed)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>0.336</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.175,0.847)</td>
<td>(-0.106,0.863)</td>
</tr>
<tr>
<td>Not working, not retired</td>
<td>0.526</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.095,1.147)</td>
<td>(-0.058,-0.880)</td>
</tr>
<tr>
<td><strong>Partner limiting health condition (ref: no)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.905**</td>
<td>-3.079**</td>
</tr>
<tr>
<td></td>
<td>(-5.223,-0.588)</td>
<td>(-5.278,-0.880)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,867</td>
<td>1,867</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-482.272</td>
<td>-481.101</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>1.010,544</td>
<td>1.006,210</td>
</tr>
</tbody>
</table>

*Note: *p<0.1; **p<0.05; ***p<0.01
each respondent has participated in, and a separate indicator is added to account for women’s age. This approach resolves the delayed entry issue, because all respondents are measured from one common point in time, and missingness within a woman’s trajectory is limited to item non-response with that arising from using a one year age metric eliminated. The discrete time event history models specified in Chapter 2 are again fitted here, to the wider sample of women aged 50 - 59, but using this time on study metric. The same sequence of estimation is followed as previously, in that the baseline hazard function is estimated first, followed by individual level, household and partner models. Results for each stage are summarised below.

The optimal baseline hazard function, in this approach, takes a quadratic form. A continuous age indicator is added to this and results are given in Model 1, Table 6.5. This initial model has three terms, with the risk of exit at a given age now a function of both the time measure and the age predictor. Note, however, that this continuous age covariate does not significantly improve the fit of the model ($\chi^2(1) = 0.0725, p = 0.7877$). According to these results, the relationship between the probability of a woman transitioning and time is adequately captured by how long she has participated in the ELSA study for and no further adjustment for age is required. This conclusion reflects a particular disadvantage of using a time on study metric; knowing the relationship between a woman’s observation time and her employment chances is of little substantive value and irrelevant to the set research questions. Previously, the baseline hazard function was estimated directly from age data which gave a more direct and meaningful representation of how the risk of employment exit evolves as women age.

Indicators for limiting health, self rated health, caring responsibilities and part time working are added, in turn, to the age model. Estimated coefficients and confidence intervals are given in Table 6.5, models 2 - 5. Of these four covariates, limiting health is significant ($\chi^2(1) = 6.3794, p = 0.01155$), as is self rated health ($\chi^2(1) = 9.9123, p = 0.001642$) and having caring responsibilities ($\chi^2(1) = 12.729, p = 0.0003$). Part time working is significant both as a main effect and age interaction term ($\chi^2(1) = 11.486, p = 0.001$). For each of these measures the estimated coefficient is positive which suggests a woman with any one given attribute will be at increased risk of transition. Decline in health was also tested, but
Table 6.5: Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, using time on study baseline hazard function with individual level covariates

<table>
<thead>
<tr>
<th></th>
<th>Baseline with age</th>
<th>Limiting health</th>
<th>Self rated</th>
<th>Caring</th>
<th>Part time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Time on study</td>
<td>1.805***</td>
<td>1.859***</td>
<td>1.836***</td>
<td>1.878***</td>
<td>1.887***</td>
</tr>
<tr>
<td></td>
<td>(1.249,2.362)</td>
<td>(1.300,2.417)</td>
<td>(1.278,2.394)</td>
<td>(1.319,2.437)</td>
<td>(1.328,2.446)</td>
</tr>
<tr>
<td>Time on study²</td>
<td>-0.229***</td>
<td>-0.232***</td>
<td>-0.226***</td>
<td>-0.233***</td>
<td>-0.239***</td>
</tr>
<tr>
<td></td>
<td>(-0.327,-0.131)</td>
<td>(-0.330,-0.133)</td>
<td>(-0.325,-0.127)</td>
<td>(-0.332,-0.134)</td>
<td>(-0.338,-0.140)</td>
</tr>
<tr>
<td>Age</td>
<td>0.010</td>
<td>-0.010</td>
<td>-0.010</td>
<td>-0.010</td>
<td>0.131**</td>
</tr>
<tr>
<td></td>
<td>(-0.061,0.080)</td>
<td>(-0.081,0.061)</td>
<td>(-0.081,0.061)</td>
<td>(-0.081,0.061)</td>
<td>(0.020,0.243)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.314**</td>
<td>-0.307**</td>
<td>-0.340**</td>
<td>-0.320**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.614,-0.013)</td>
<td>(-0.609,-0.005)</td>
<td>(-0.642,-0.038)</td>
<td>(-0.620,-0.020)</td>
<td></td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.035</td>
<td>-0.001</td>
<td>-0.029</td>
<td>-0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.381,0.310)</td>
<td>(-0.348,0.346)</td>
<td>(-0.376,0.319)</td>
<td>(-0.357,0.333)</td>
<td></td>
</tr>
<tr>
<td>Social class</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(ref: managerial/professional)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.222</td>
<td>0.221</td>
<td>0.220</td>
<td>0.138</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.103,0.547)</td>
<td>(-0.104,0.546)</td>
<td>(-0.105,0.545)</td>
<td>(-0.194,0.469)</td>
<td></td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>0.123</td>
<td>0.108</td>
<td>0.134</td>
<td>0.010</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.221,0.467)</td>
<td>(-0.238,0.454)</td>
<td>(-0.210,0.479)</td>
<td>(-0.343,0.364)</td>
<td></td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.063*</td>
<td>-0.063*</td>
<td>-0.065*</td>
<td>-0.050</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.129,0.003)</td>
<td>(-0.128,0.002)</td>
<td>(-0.131,0.001)</td>
<td>(-0.119,0.019)</td>
<td></td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.247</td>
<td>-0.233</td>
<td>-0.219</td>
<td>-0.261</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.563,0.068)</td>
<td>(-0.548,0.083)</td>
<td>(-0.535,0.096)</td>
<td>(-0.576,0.054)</td>
<td></td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.373***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.093,0.652)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td></td>
<td>0.585***</td>
<td>(0.243,0.926)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td></td>
<td></td>
<td>0.508***</td>
<td>(0.240,0.776)</td>
<td></td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.631***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.849,2.412)</td>
</tr>
<tr>
<td>Age:Part time</td>
<td></td>
<td>-0.202**</td>
<td></td>
<td></td>
<td>(-0.321,-0.083)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-5.910***</td>
<td></td>
<td></td>
<td>(-6.945,-4.874)</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.637***</td>
<td>-4.361**</td>
<td>-4.315**</td>
<td>-4.394**</td>
<td>-5.910***</td>
</tr>
<tr>
<td></td>
<td>(-9.315,-1.960)</td>
<td>(-8.123,-0.599)</td>
<td>(-8.082,-0.548)</td>
<td>(-8.162,-0.627)</td>
<td>(-6.945,-4.874)</td>
</tr>
<tr>
<td>Observations</td>
<td>3.399</td>
<td>3.399</td>
<td>3.399</td>
<td>3.399</td>
<td>3.399</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-909.864</td>
<td>-899.624</td>
<td>-897.858</td>
<td>-896.449</td>
<td>-892.132</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>1.827,727</td>
<td>1.821,248</td>
<td>1.817,715</td>
<td>1.814,899</td>
<td>1.808,265</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
not found significant ($\chi^2(1) = 0.2456, p = 0.6202$).

Household level covariates are incorporated into the final individual level specification and results are given in Table 6.6. Of the household measures of namely tenure, pension wealth and non pension wealth, tenure is significant ($\chi^2(2) = 8.2806, p = 0.01592$), but the wealth variables are not. Compared to women residing in homes owned outright, the probability of exit for those with an outstanding mortgage is predicted to be 26.9% lower. The risk differential associated with renting is negative, but smaller in magnitude at approximately 1.6%. There is no evidence of an association between the level of pension or non pension wealth in the household and the probability that the female partner leaves work; women are predicted the same level of risk irrespective of the wealth resources accumulated by herself and her partner.

Indicators for male spousal attributes are added to the household model containing tenure, and results are given in Table 6.7 (page 232). The partner control variables of income and age are incorporated into the model, with partner’s employment status added next (Model 1). A measure of partner health is incorporated in Model 2. Results show no evidence that the male spouse’s employment status predicts women’s exit ($\chi^2(2) = 3.9299, p = 0.1402$); this indicates that women partnered to men who are out of work have the same probability of exit as women with working partners. Similarly the male partner’s limiting health status does not influence the likelihood of a transition occurring ($\chi^2(1) = 1.7997, p = 0.1797$). Women coupled to a man with a limiting health condition have a similar level of transition risk as women partnered to men without such a limitation.

In the next section the results summarized here are considered alongside those from the original analysis presented in Chapter 3, and those from Section 6.3.2 above.

6.4 Summary and conclusion

The main analysis of this thesis, which was presented in Chapter 3, structured the retirement process along a yearly age axis, with models for women’s transitions out of employment fitted to a truncated sample containing respondents who entered the study after the age of 50. The decision to configure on an age axis, and to include delayed entry women, had implications for the occurrence and incidence of missing data in the analysed sample. As was raised
Table 6.6: Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, using time on study baseline hazard function with household level covariates

<table>
<thead>
<tr>
<th></th>
<th>Tenure</th>
<th>Household pension wealth</th>
<th>Household non pension wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Time on study</td>
<td>1.889***</td>
<td>1.928***</td>
<td>1.885***</td>
</tr>
<tr>
<td></td>
<td>(1.329,2.450)</td>
<td>(1.368,2.488)</td>
<td>(1.325,2.445)</td>
</tr>
<tr>
<td>Time on study(^2)</td>
<td>-0.232***</td>
<td>-0.239***</td>
<td>-0.233***</td>
</tr>
<tr>
<td></td>
<td>(-0.332,-0.133)</td>
<td>(-0.338,-0.140)</td>
<td>(-0.332,-0.134)</td>
</tr>
<tr>
<td>Age</td>
<td>0.118**</td>
<td>0.115**</td>
<td>0.117**</td>
</tr>
<tr>
<td></td>
<td>(0.005,0.230)</td>
<td>(0.002,0.227)</td>
<td>(0.004,0.229)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td>-0.324**</td>
<td>-0.338**</td>
<td>-0.342**</td>
</tr>
<tr>
<td>O level equivalent</td>
<td>-0.627,-0.020</td>
<td>-0.644,-0.032</td>
<td>-0.647,-0.038</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>-0.027</td>
<td>-0.095</td>
<td>-0.102</td>
</tr>
<tr>
<td></td>
<td>(-0.379,0.325)</td>
<td>(-0.461,0.271)</td>
<td>(-0.459,0.256)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td>0.076</td>
<td>0.105</td>
<td>0.097</td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.257,0.410</td>
<td>(-0.233,0.443)</td>
<td>(-0.236,0.430)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>-0.110</td>
<td>-0.047</td>
<td>-0.037</td>
</tr>
<tr>
<td></td>
<td>(-0.472,0.252)</td>
<td>(-0.416,0.322)</td>
<td>(-0.406,0.332)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>-0.044</td>
<td>-0.046</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(-0.113,0.025)</td>
<td>(-0.115,0.023)</td>
<td>(-0.112,0.024)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>-0.230</td>
<td>-0.238</td>
<td>-0.255</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td>0.227</td>
<td>0.223</td>
<td>0.219</td>
</tr>
<tr>
<td></td>
<td>(-0.079,0.533)</td>
<td>(-0.083,0.530)</td>
<td>(-0.087,0.525)</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td>0.537***</td>
<td>0.549***</td>
<td>0.576***</td>
</tr>
<tr>
<td></td>
<td>(0.161,0.914)</td>
<td>(0.172,0.927)</td>
<td>(0.195,0.956)</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.476***</td>
<td>0.469***</td>
<td>0.493***</td>
</tr>
<tr>
<td></td>
<td>(0.207,0.745)</td>
<td>(0.200,0.739)</td>
<td>(0.222,0.764)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>1.594***</td>
<td>1.580***</td>
<td>1.547***</td>
</tr>
<tr>
<td></td>
<td>(0.806,2.381)</td>
<td>(0.793,2.368)</td>
<td>(0.759,2.335)</td>
</tr>
<tr>
<td>Age:part time</td>
<td>-0.202***</td>
<td>-0.201***</td>
<td>-0.197***</td>
</tr>
<tr>
<td></td>
<td>(-0.322,-0.083)</td>
<td>(-0.321,-0.082)</td>
<td>(-0.317,-0.077)</td>
</tr>
<tr>
<td>Tenure (ref: owns hoe outright)</td>
<td>-0.349***</td>
<td>-0.336***</td>
<td>-0.315***</td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>-0.594,-0.104</td>
<td>(-0.581,-0.090)</td>
<td>(-0.563,-0.086)</td>
</tr>
<tr>
<td>Rents</td>
<td>-0.021</td>
<td>-0.017</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>(-0.512,0.470)</td>
<td>(-0.514,0.480)</td>
<td>(-0.494,0.601)</td>
</tr>
<tr>
<td>Household pension wealth (ref: wealthiest)</td>
<td>-0.186</td>
<td>-0.186</td>
<td>-0.353</td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>-0.572,0.199</td>
<td>-0.572,0.199</td>
<td>-0.572,0.199</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>-0.345</td>
<td>-0.345</td>
<td>-0.345</td>
</tr>
<tr>
<td>Middle quintile</td>
<td>-0.547***</td>
<td>-0.547***</td>
<td>-0.547***</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>-0.312</td>
<td>-0.312</td>
<td>-0.312</td>
</tr>
<tr>
<td>Household non pension wealth quintile</td>
<td>-0.678,0.055</td>
<td>-0.678,0.055</td>
<td>-0.678,0.055</td>
</tr>
<tr>
<td>Poorest quintile</td>
<td>-0.353</td>
<td>-0.353</td>
<td>-0.353</td>
</tr>
<tr>
<td>Second poorest quintile</td>
<td>-0.443**</td>
<td>-0.443**</td>
<td>-0.443**</td>
</tr>
<tr>
<td>Middle quintile</td>
<td>-0.273</td>
<td>-0.273</td>
<td>-0.273</td>
</tr>
<tr>
<td>Second wealthiest quintile</td>
<td>-0.590**</td>
<td>-0.590**</td>
<td>-0.590**</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.837***</td>
<td>-5.600***</td>
<td>-5.590***</td>
</tr>
<tr>
<td></td>
<td>(-6.899,-4.775)</td>
<td>(-6.691,-4.509)</td>
<td>(-6.668,-4.512)</td>
</tr>
<tr>
<td>Observations</td>
<td>3,399</td>
<td>3,399</td>
<td>3,399</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-875.968</td>
<td>-871.751</td>
<td>-873.235</td>
</tr>
<tr>
<td>Akaiake Inf. Crit.</td>
<td>1,785.936</td>
<td>1,785.503</td>
<td>1,788.470</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
Table 6.7: Parameter estimates from discrete time event history models for the conditional probability of women’s transition from employment, using time on study baseline hazard function with partner level covariates

<table>
<thead>
<tr>
<th></th>
<th>Partner’s employment</th>
<th>Partner’s limiting health</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Time on study</td>
<td>1.899***</td>
<td>1.892***</td>
</tr>
<tr>
<td></td>
<td>(1.338,2.460)</td>
<td>(1.330,2.453)</td>
</tr>
<tr>
<td>Time on study^2</td>
<td>−0.235***</td>
<td>−0.234***</td>
</tr>
<tr>
<td></td>
<td>(−0.335,−0.136)</td>
<td>(−0.334,−0.134)</td>
</tr>
<tr>
<td>Age</td>
<td>0.116*</td>
<td>0.111*</td>
</tr>
<tr>
<td></td>
<td>(0.002,0.229)</td>
<td>(−0.003,0.224)</td>
</tr>
<tr>
<td>Age:part time</td>
<td>−0.205***</td>
<td>−0.202***</td>
</tr>
<tr>
<td></td>
<td>(−0.325,−0.085)</td>
<td>(−0.322,−0.082)</td>
</tr>
<tr>
<td>Education (ref: less than O level)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>O level equivalent</td>
<td>−0.315**</td>
<td>−0.321**</td>
</tr>
<tr>
<td></td>
<td>(−0.620,−0.010)</td>
<td>(−0.625,−0.016)</td>
</tr>
<tr>
<td>Higher than A level equivalent</td>
<td>−0.050</td>
<td>−0.037</td>
</tr>
<tr>
<td></td>
<td>(−0.406,0.307)</td>
<td>(−0.392,0.318)</td>
</tr>
<tr>
<td>Social class (ref: managerial/professional)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate occupations</td>
<td>0.066</td>
<td>0.069</td>
</tr>
<tr>
<td></td>
<td>(−0.268,0.400)</td>
<td>(−0.265,0.403)</td>
</tr>
<tr>
<td>Routine/manual occupations</td>
<td>−0.123</td>
<td>−0.122</td>
</tr>
<tr>
<td></td>
<td>(−0.487,0.241)</td>
<td>(−0.486,0.241)</td>
</tr>
<tr>
<td>Individual income (log)</td>
<td>−0.046</td>
<td>−0.045</td>
</tr>
<tr>
<td></td>
<td>(−0.117,0.024)</td>
<td>(−0.115,0.025)</td>
</tr>
<tr>
<td>Dependent child (ref: no)</td>
<td>−0.238</td>
<td>−0.221</td>
</tr>
<tr>
<td></td>
<td>(−0.556,0.081)</td>
<td>(−0.539,0.097)</td>
</tr>
<tr>
<td>Limiting health condition (ref: no)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.238</td>
<td>0.219</td>
</tr>
<tr>
<td></td>
<td>(−0.068,0.544)</td>
<td>(−0.087,0.525)</td>
</tr>
<tr>
<td>Poor self rated health (ref: good or better)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.528***</td>
<td>0.517***</td>
</tr>
<tr>
<td></td>
<td>(0.152,0.904)</td>
<td>(0.139,0.895)</td>
</tr>
<tr>
<td>Recently provided care (ref: no)</td>
<td>0.442***</td>
<td>0.440***</td>
</tr>
<tr>
<td></td>
<td>(0.168,0.717)</td>
<td>(0.166,0.714)</td>
</tr>
<tr>
<td>Part time (ref: full time)</td>
<td>1.599***</td>
<td>1.595***</td>
</tr>
<tr>
<td></td>
<td>(0.810,2.387)</td>
<td>(0.807,2.383)</td>
</tr>
<tr>
<td>Tenure ref: owns home outright</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has outstanding mortgage</td>
<td>−0.313**</td>
<td>−0.329***</td>
</tr>
<tr>
<td></td>
<td>(−0.563,−0.062)</td>
<td>(−0.578,−0.079)</td>
</tr>
<tr>
<td>Rent</td>
<td>−0.017</td>
<td>−0.059</td>
</tr>
<tr>
<td></td>
<td>(−0.511,0.477)</td>
<td>(−0.555,0.437)</td>
</tr>
<tr>
<td>Partner income (log)</td>
<td>0.0001</td>
<td>−0.004</td>
</tr>
<tr>
<td></td>
<td>(−0.058,0.059)</td>
<td>(−0.061,0.054)</td>
</tr>
<tr>
<td>Partner age</td>
<td>−0.002</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(−0.029,0.024)</td>
<td>(−0.017,0.031)</td>
</tr>
<tr>
<td>Partner employment status (ref: employed)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Retired</td>
<td>0.345*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−0.001,0.690)</td>
<td></td>
</tr>
<tr>
<td>Not working, not retired</td>
<td>0.179</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−0.249,0.607)</td>
<td></td>
</tr>
<tr>
<td>Partner limiting health condition (ref: no)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.187</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−0.084,0.458)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>−5.742***</td>
<td>−6.217***</td>
</tr>
<tr>
<td></td>
<td>(−7.518,−3.966)</td>
<td>(−7.919,−4.516)</td>
</tr>
<tr>
<td>Observations</td>
<td>3,399</td>
<td>3,399</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−873.746</td>
<td>−874.812</td>
</tr>
<tr>
<td>Akaiake Inf. Crit.</td>
<td>1,789.493</td>
<td>1,789.623</td>
</tr>
</tbody>
</table>

*p<0.1; **p<0.05; ***p<0.01
in the introduction to this chapter missing data can cause bias in parameter estimates and weaken the generalizability of results, whilst removal of cases containing unknown values can decrease statistical power and increase uncertainty (Dong and Peng, 2013).

In the selected ELSA sample, missingness occurred at the beginning of employment sequences for delayed entry respondents, and this was addressed by modelling under a conditional likelihood framework in which it was assumed that the first transition observed was the first that occurred. Unknown values that occurred within a woman’s observation window were a consequence of both item non response and of adopting a one year age axis for positioning observations. ELSA participants were interviewed at minimum two yearly intervals but from different entry ages and this led to a complex pattern of observations and missing data when configured along a one yearly age axis. Missingness arising from this was dealt with using a version of the ‘last value carried forward’ method after which any records still containing unknown values were removed. Models were subsequently fitted to the resulting complete cases sample.

In this chapter, we returned to decisions made during the earlier analysis of Chapter 3, that concern the methods used for dealing with missingness, and investigated the viability of alternative approaches. As an alternative to modelling under a conditional likelihood assumption single and multiple imputation methods were attempted; however neither were satisfactory. Single imputation does not account for variability in the outcome whereas multiple imputation failed due to the scarcity of events in the wide form of the dataset. However multiple imputation for binary outcomes on a person-period dataset requires multilevel imputation methods and associated time and computing resources that go beyond what is available for this thesis.

Given the limitations of imputation in this context we then detailed how a more restrictive sampling strategy and restructured age axis could reduce the incidence of missingness. In this scenario only women observed from the age of 50 - 52 were included in the sample with delayed entry respondents deleted. This reduced the number of households studied from 1569 to 771, but removed the delayed entry problem and need for the associated assumption that women were in continuous employment between the age of 50 and entry to ELSA. A compressed age axis was also used to reduce the incidence of missingness within the obser-
vation window. The discrete time event history model for women’s transitions specified in Chapter 3 were estimated again under these conditions and results presented in Section 6.3.2.

The final approach for addressing missing data was to consider estimates and results arising from event history models using an alternative metric for time, rather than age. A time on study metric is advantageous in that it retains a larger sample size, whilst eliminating missingness from the beginning of the observed trajectories, and unknown values within the observation window are limited to item non response. Age entered the model not through the baseline hazard, but as a continuous predictor. Results from models estimated with this structure, using age as a continuous measure, were given in Section 6.3.3. The aim of the following discussion is to compare and contrast findings from the three different versions of discrete time models

6.4.1 Comparison of parameter estimates under different time and sample configurations

Table 6.8 summarizes the coefficients and standard errors for selected covariates from each of the three sets of event history models constructed. In each case the event of interest is women’s transition out of employment, and the results from the original model presented in Chapter 3 are given in the first column. This model was estimated from a delayed entry sample of 1569 women aged between 50 and 59 on entry using a one year age scale. In the second column are estimates from the sample containing the 771 women observed from one common entry point, of age 50 - 52; this model was specified using an interval age axis and no delayed entry respondents were in the sample. Results from the third version, which is based on 1495 households, are given in the final column. These coefficients are from the model with a time on study baseline hazard, age is included as a continuous covariate and missingness arises only from item non response.

Of particular interest here is the sensitivity of parameter estimates to the choice of time scale and the inclusion of delayed entry participants. The first point to note in Table 6.8 is the difference in the variables that are statistically significant, at the 5% level, across the three models. When the sample included only women observed from ages 50 - 52 and an interval age scale was used, the limiting health and tenure covariates are not significant at the 5% level
Table 6.8: Significant coefficients and standard errors from event history models for predicting women’s transition under different sample selection criteria and time metrics

<table>
<thead>
<tr>
<th>Covariate</th>
<th>One year age scale</th>
<th></th>
<th>Interval age scale</th>
<th></th>
<th>Time on study scale</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Age 50 - 59 at baseline</td>
<td>n = 1569</td>
<td>Age 50 - 52 at baseline</td>
<td>n = 771</td>
<td>Age 50 - 59 at baseline</td>
<td>n = 1495</td>
</tr>
<tr>
<td></td>
<td>( \hat{\beta} )</td>
<td>se(( \hat{\beta} ))</td>
<td>( \hat{\beta} )</td>
<td>se(( \hat{\beta} ))</td>
<td>( \hat{\beta} )</td>
<td>se(( \hat{\beta} ))</td>
</tr>
<tr>
<td>Limiting health</td>
<td>0.228</td>
<td>0.213</td>
<td>–</td>
<td>–</td>
<td>0.227</td>
<td>0.156</td>
</tr>
<tr>
<td>Self rated health</td>
<td>0.556</td>
<td>0.235</td>
<td>0.667</td>
<td>0.263</td>
<td>0.537</td>
<td>0.192</td>
</tr>
<tr>
<td>Caring</td>
<td>0.486</td>
<td>0.172</td>
<td>–</td>
<td>–</td>
<td>0.476</td>
<td>0.137</td>
</tr>
<tr>
<td>Part time</td>
<td>1.573</td>
<td>0.434</td>
<td>1.109</td>
<td>0.348</td>
<td>1.594</td>
<td>0.402</td>
</tr>
<tr>
<td>Part time:Age (continuous)</td>
<td>-0.183</td>
<td>0.066</td>
<td>–</td>
<td>–</td>
<td>-0.202</td>
<td>0.061</td>
</tr>
<tr>
<td>Part time:Age 53/54</td>
<td>–</td>
<td>–</td>
<td>-0.800</td>
<td>0.471</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Part time:Age 55/56</td>
<td>–</td>
<td>–</td>
<td>-0.201</td>
<td>0.532</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Part time:Age 57/58/59</td>
<td>–</td>
<td>–</td>
<td>-1.472</td>
<td>0.524</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Mortgage</td>
<td>-0.374</td>
<td>0.168</td>
<td>–</td>
<td>–</td>
<td>-0.349</td>
<td>0.125</td>
</tr>
<tr>
<td>Rent</td>
<td>-0.184</td>
<td>0.337</td>
<td>–</td>
<td>–</td>
<td>-0.021</td>
<td>0.250</td>
</tr>
<tr>
<td>Household pension wealth</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Household non pension wealth 1</td>
<td>–</td>
<td>–</td>
<td>-0.571</td>
<td>0.300</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Household non pension wealth 2</td>
<td>–</td>
<td>–</td>
<td>-0.992</td>
<td>0.302</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Household non pension wealth 3</td>
<td>–</td>
<td>–</td>
<td>-0.217</td>
<td>0.240</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Household non pension wealth 4</td>
<td>–</td>
<td>–</td>
<td>-0.285</td>
<td>0.236</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Partner retired</td>
<td>0.456</td>
<td>0.223</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Partner not working nor retired</td>
<td>0.170</td>
<td>0.281</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Partner health</td>
<td>–</td>
<td>–</td>
<td>0.485</td>
<td>0.193</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

- denotes \( p > 0.05 \)
whereas they were in the one year age scale and time on study specifications. The results for male partner health and household non pension wealth also conflict with a significant effect found in this interval axis version, but not in the alternatives. There is less disparity between the original one year age scale version and the time on study specification, with the only difference in the conclusion for male partner’s employment status. It is significant in the one year age scale model, but not when the time on study axis is used.

Now, comparing effect sizes of the covariates in the original yearly age axis version with the time on study model, and the predicted increase in hazard associated with having a limiting health condition, poor self rated health, caring responsibilities, part time working or an outstanding mortgage is similar irrespective of the time metric used. Variability in estimates, however, is lower in the time on study axis as evidenced by smaller standard errors. There is some difference in the tenure variable with renting associated with higher risk in the time on study version.

### 6.4.2 Positioning observations under different time structures

The above comparison of results from different discrete time event history models demonstrates that inference can change according to the sampling strategy and time metric used in the analysis. If delayed entry respondents are included in the sample, then the units and number of time points of the axis determines the positioning and alignment of these observations. This is explained further with reference to Figure 6.2 on page 212. The most common observation patterns shown in this figure were respondents measured on either two or three occasions; 6.9% of women have responses at ages 56 and 58; 5.6% at 54, 56 and 58 with 5.5% observed at 55, 57, 59. In the original analysis of women’s transitions in Chapter 3 the data from these participants was aligned with other women of the same age and this will be reflected in the form of the fitted baseline hazard function. Additionally, with this age structure a woman’s time varying covariate measures, such as health and wealth, are aligned with those of others that are the same age. This is important because the effect of a time varying measure might change with age; the influence of a limiting health condition at age 51, for example, might differ from that at age 59. Using an age axis ensures the effect of these measures is isolated from any underlying impact of age.
Figure 6.4: Distribution of women by age at each observation point

When a time on study axis is used the trajectories of these partially observed women will start from the far left of the axis and missingness at the beginning and within their sequences are removed; consequently their measurements are aligned with those of younger women. A time on study axis will have five time points, reflecting the use of five waves of ELSA data for this research. Figure 6.4 shows the distribution of women’s ages at each point. For convenience women have been categorised into one of four groups according to the age that they were on that particular observation. Forty six percent of the sample of women when they first entered ELSA were aged either 51 or 52; 25% were aged 53 or 54, 18% aged 55 or 56 with the remaining 11% women aged between 57 and 59 inclusive. At the time of their second ELSA response, 3% of the sample were aged 51 or 52, 42% were 53 or 54, 26% aged 55 or 56 and the final 28% were either 57, 58 or 59. As would be expected, most of the sample members who were observed on four or five occasions are aged 57 or over.

Figure 6.4 highlights the shortcomings of using a time on study axis in an event history model. For the purposes of this research comparing the characteristics of women at the time of their first ELSA questionnaire - or their second, third or fourth - has little substantive meaning. Note also the dispersement of the oldest women across the observation points; these are delayed entry cases and when a single age axis was used their employment and covariate data was compared with women of the same age. Now, however, their measurements are compared with younger women. Eleven percent of the sample at the first point of
observation and 28% at the second point is women aged 57, 58 or 59. Their time varying
covariates, including health and pension wealth, are now aligned with women aged between
51 and 56. These older persons may contribute a relatively high proportion of transitions
to the dataset at these earlier times, and this will impact on the shape of the resulting base-
line hazard function. The positioning of the delayed entry cases is, therefore, central to the
estimation and fitting of the discrete time models.

Of the three model versions considered here - of yearly age, interval age and time on
study - the time on study metric is the most straightforward with regards to data preparation;
however this advantage is lost in the subsequent model fitting and interpretation stages. If the
process under study is theorized to evolve with age then obtaining meaningful substantive
results is more complex and less efficient from a time on study model than from one specified
with an age metric. Constructing trajectories and an overall risk profile for employment exit,
covering the entire age range of interest and from a time on study specification, involves
merging results from different survival curves. Literature surrounding the choice of time
axis in discrete time event history models advocates the use of a ‘meaningful’ metric (Singer
and Willett, 2003) which, in the context of retirement, would be age and not time on study;
although reasons cited for this relate to ease of substantive interpretation rather than any
rigorous theoretical proof. Research from other disciplines, specifically epidemiology and
medical statistics, examines this issue using formal mathematical methods, but in continuous
time, rather than discrete time applications (Kom et al., 1997; Lamarca et al., 1998; Sperrin
and Buchan, 2013). Results from those fields are conflicting with some recommending age,
but others supporting the use of other alternative metrics.

In this chapter, our aim was not to present any formal proof relating to choice of time
scale or model specification. Rather the objective was to illustrate how, in the context of
women’s retirement, parameter estimates can vary according to the time metric used. With
this, we argue for the development of a more rigorous study that compares inference from
discrete time event history models under various sampling and modelling conditions. This is
particularly pertinent for the analysis of longitudinal studies such as ELSA, where the analyst
is faced with multiple complex choices with regards to sample selection and choice of time
metric. Evidence presented here suggests that the removal of delayed entry participants
may have a greater impact on results than the choice of time scale. However developing a theoretical proof in support of this goes beyond the scope of this thesis, and we limit our conclusion to the tentative claim that modelling retirement with an age structure that includes delayed entry participants is the most appropriate and preferred of the three options studied.
Chapter 7

Discussion

7.1 Introduction

There is an emerging body of literature concerning older women’s working patterns in the United Kingdom. Findings from recent qualitative studies indicate that women tend to follow non standard routes out of work with trajectories defined by partner circumstances, domestic responsibilities and financial need (Loretto and Vickerstaff, 2013; Duberley et al., 2014). Quantitative retirement research using large scale UK datasets, however, is focused on male trajectories and concentrates on factors relating to individual characteristics with little consideration given to the wider domestic context. The relationship between pension entitlement and male employment transitions has been considered (Blundell and Johnson, 1999), but the association with women’s retirement has not been widely investigated. Current literature recognises gender differences in pension resources, with women likely to have fewer pension rights than their male counterparts, and this can lead to dependency on joint resources in retirement (Ginn and Arber, 1993,1999). In this thesis, discrete time event history models are fitted to data from the English Longitudinal Study of Ageing to establish the effect of partner and household attributes, including pension wealth, on employment transitions for women aged between 50 and 59.

The first objective of this research was to formally test and quantify the impact of partner health, partner’s employment status and household pension wealth on the probability of women’s employment transitions prior to state pension age. Our second objective was to consider evidence for the differential impact of these factors across heterogeneous exit
pathways. The first of these pathways involves voluntary transitions and is characterised by women who identify as retired after any exit that occurs. The second is identified by the involuntary exit of women who report either long term illness, a caring role or unemployment as their destination state. The third aim of this research was to determine whether the same factors that influence women’s work transitions also impact on the employment patterns of the male partners in the same households. Specifically, we hypothesised that male partner health has a greater impact on the woman’s continued employment than woman’s health does on the male couple member’s probability of exit. Results show that poor self rated health and having a retired partner are the most influential risk factors for women’s employment exit, with limiting health and a partner in an alternative inactive state also associated with higher risk. A couple's combined pension wealth determines the likelihood of women’s involuntary, rather than voluntary, exit with those in the poorest 40% of households at greatest risk. No statistically significant association was found between women’s conditional probability of labour force exit and partner health.

This research is unique in that quantitative methods are used to examine the impact of joint pension wealth, and other household and partner characteristics, on women’s retirement trajectories in England. Women’s retirement data has been analysed in several international settings, including the United States and Germany (Blau and Riphahn, 1999; Szinovacz and Deviney, 2000; Drobnic, 2002). However these countries have different pension and social security structures from the UK, and whilst they provide a useful basis for comparing the predictors of women’s labour market exit, it cannot be assumed that findings apply to women here. State pension in the UK is less generous than other European countries and is based on a contributory system that encourages private provision (Blundell et al., 2002). However access to private pensions is associated with certain occupational groups, and part time working, lower incomes and discontinuous work histories can further limit women’s private pension wealth (Ginn and Arber, 2002). Women consequently tend to accumulate, on average, less pension resources than their male counterparts and this encourages dependence on the spouse or partner for financial wellbeing in later life. The reliance on disability insurance to provide an early exit pathway out of the labour market is also a feature of UK later life employment patterns that is not necessarily seen elsewhere. Formal early retire-
ment provision in the United Kingdom may be possible through occupational and private pensions, but is not a feature of state provided support. This thesis further develops the currently limited quantitative analysis of women’s retirement in England and positions findings within the above cited international body of literature.

This chapter is structured as follows. An overview of results is given in the next section and the pertinent features of the modelled women’s employment pathways are presented. In Section 7.3 we develop the discussion of how a woman’s domestic environment interacts with her employment domain to influence her transition from work. In Section 7.4 we highlight the contributions of the methods used in this analysis of women’s transitions to both our findings and the wider field of women’s retirement studies. In Section 7.5 the focus is on the influence of household circumstances on the subsequent pathway taken after a woman’s exit and policy implications are considered in Section 7.6. Limitations and recommendations for future research are given in Section 7.7, whilst Section 7.8 concludes.

7.2 The later life employment trajectories of older women

Current studies of coupled women’s retirement pathways emphasise the complexity of their work patterns, with the timing and nature of transitions determined by dynamic interactions between the domestic and work environments (Loretto and Vickerstaff, 2013; Duberley et al., 2014). These small scale qualitative studies identify partner health, a non working partner, and the need to provide care to family members as influential household factors for women’s labour force transitions. Amongst women interviewed in these studies, understanding of long term financial issues and pension provision was poor, and often the responsibility of the male spouse. Our results correlate with these in that male partner’s labour market status and family caring needs are established as significant predictors of women’s employment exit, but we find no evidence that partner health has a statistically significant effect. Household pension wealth is shown to influence women’s retirement pathways, but not with respect to the timing of their exit; rather, it determines the nature of the transition and pathway followed through to state pension age.

Two distinct pathways for women’s labour market exit prior to state pension age are established. The first is an involuntary route characterised by exit into a state of caring, illness
or unemployment, whilst the second is a voluntary pathway defined by reported retirement prior to 60. These pathways are depicted in Figure 7.1 which is reproduced for convenience from Chapter 4. The central solid line plots a trajectory of continuous employment between the age of 50 and women’s state pension age of 60. In theory, this is the route that older working women should follow as there is no formal early retirement provision in the United Kingdom. However women on the involuntary pathway tend to leave work at age 54/55 - that is, five to six years prior to eligibility for the state pension age - and enter an alternative labour market state of either illness, caring or unemployment. Women who enter one of these states after exit are likely to remain in it; they typically report as retired only upon reaching age 60. This trajectory is depicted by the upper dashed line in Figure 7.1. We found that of the 1569 women studied in this research 81.7% remained in employment, whilst 9.8% followed this alternative pathway. The second early exit route differs in that women are likely to transition later, at age 56/57, and report as retired immediately thereafter. From the sampled ELSA households 8.5% of women followed this trajectory. The majority of these continue to identify as retired with few likely to change their status to any of the alternative options. This voluntary pathway is shown visually by the lower dotted line in Figure 7.1. Across the two pathways, the incidence of return to employment is low. Forty women from the 1569 households, or 2.5%, show an alternating pattern of employment and non employment by returning to work after leaving. Eleven of these returned from retirement and the remainder from involuntary states.

![Figure 7.1: Older women’s pathways to retirement](image-url)
This identification of voluntary and involuntary pathways has been possible because of the theoretical and methodological approaches used in this thesis. In the theoretical framework, that was first explained in Chapter 1, retirement was conceptualised as a dynamic process rather than an abrupt event. Representing retirement in this way involved constructing a time axis along which employment and other associated trajectories could be positioned. Of the three possible time measures of age, calendar year and time on study we selected the first; age is the most substantively meaningful of these options with women’s employment status likely to depend more on this measure than either of the alternatives. Modelling later life employment trajectories as an ageing process allowed us to conduct a more detailed analysis of how the risk of early exit develops as women approach state pension age, and led to the identification of the pathways described here. Few studies, however, model retirement along an age timeline; with the exception of Drobnič (2002) and Madero-Cabib et al. (2016) other analytic approaches are based on the alternative time measures and, as such, place less emphasis on the timing of transitions and focus more on the factors that predict such events (Blau and Riphahn, 1999; Szinovacz et al., 2001; Pienta, 2003). By modelling retirement as an ageing process we are consistent with the methodology used in the most recent longitudinal analyses of later life employment (Madero-Cabib et al., 2016), and have constructed a more comprehensive picture of older women’s retirement patterns by identifying the different pathways described here.

The attributes that determine the likelihood that a woman leaves work prior to state pension age are considered in detail in the next section, and further discussion on the methods used for that analysis follows in Section 7.4. Predictors of the type of transition and pathway followed to retirement are the subject of Section 7.5.

7.3 Predictors of older women’s transitions out of employment

Recent literature emphasises the need for retirement research to consider the wider domestic context rather than take a more limited individualistic view (Loretto and Vickerstaff, 2013; Duberley et al., 2014). The research questions of this thesis reflect this, and consider the
influence of partner and household attributes on older women’s transitions out of work. Our results show that women who have recently provided care, have poor health or a non-working partner are more likely to leave work and take one of the alternative pathways shown in Figure 7.1, rather than remain in employment until state pension age. In this section these results are positioned within the relevant literature surrounding women’s retirement and with reference to the predictors of male partner transitions. Findings relating to the individual level characteristics of interest are considered next with household and partner attributes following that.

### 7.3.1 The effect of caring and health on the probability of employment exit

Providing care increases the conditional probability that an older woman leaves work prior to 60 by an estimated 63%; male partner trajectories, however, are unaffected with spouse’s age of exit not determined by any caring duties they may have. This result provides statistically significant evidence in support of conclusions surrounding care obligations drawn from small scale UK qualitative studies (Loretto and Vickerstaff, 2013; Duberley et al., 2014), but additionally we evaluate the magnitude of the caring effect. Given that the women in our study are primarily caring for relatives - 18% look after their spouse, 12% their child, 16% a grandchild and 41% their parent - this finding provides robust evidence for the hypothesis of dependency of women’s employment on family obligations.

Statistically significant associations between older women’s health and their transition probability, as well as between male partner’s health and their own continued employment are found in this research. If an older woman has a limiting health condition then her risk of exit is raised by an estimated 25.6% irrespective of age, and women who self evaluate their health to be poor have a probability of leaving work that is approximately 74.4% higher than those who rate their health as good or better. The limiting health effect is also present amongst male partners, but differs in magnitude from that estimated for the female spouses; a male partner with a limiting condition has a much higher increased transition risk of approximately 149%, but with a 12.8% downwards adjustment per year. The effect of poor health for male partners is greatest at younger ages, but constant for women.
This greater effect of limiting health on the male spouses’ compared to women’s transition probability may reflect men’s greater reliance on disability insurance as a means of leaving the labour market prior to state pension age. There is no formal early retirement provision in the United Kingdom, meaning exit before state pension age is contingent on sufficient personal financial resources or claiming unemployment or disability payments. Eligibility criteria for disability support are less stringent than those for unemployment and this has consequently become the more prominent pathway of the two. However there is a gender bias amongst disability claimants; because eligibility is contingent on sufficient contribution years this can exclude women with shorter or discontinuous employment records. Men, consequently, comprise a greater proportion of recipients (Banks et al., 2011). Banks and Smith (2006) assert that receipt of disability and illness benefits may be linked to self reported health. It then follows that the larger effect of a limiting condition on men’s, rather that women’s transitions shown in our research reflect their greater dependence, and women’s lower level of reliance, on disability insurance as an early retirement vehicle. This conclusion highlights a methodological advantage of this thesis. In the fitting of event history models for transitions the effect of health is measured, and this allows the magnitude of effect to be compared between women and their partners. This quantification of the health influence is not possible where qualitative methods are used, as seen elsewhere in UK women’s retirement literature (Loretto and Vickerstaff, 2013; Duberley et al., 2014).

7.3.2 The effect of partner and household attributes on older women’s employment transitions

Here we consider the partner and household attributes of health, partner’s employment status and pension wealth, as raised in the third research question.

7.3.2.1 Partner health

No evidence was found to support the hypothesis that male partner health predicts the occurrence or timing of older women’s early labour market exit, which suggests that women coupled to men with limiting health conditions are no more or less likely to leave work than women partnered to healthy men. This finding is consistent with that of Szinovacz and
Deviney (2000). Women, they contend, are able to juggle both caring needs with market work in later life, because it is a continuation of earlier life course circumstances. Poor health of the male partner, therefore, will not necessarily lead to women’s employment exit prior to the state pension age. An alternative explanation is that the insignificant effect of spousal health is a consequence of two conflicting theories relating to older women’s roles in the household. In the advent of poor partner health a woman might either leave work to provide necessary care or, alternatively, she may remain in employment to ensure the financial wellbeing of the family. In the latter of these two circumstances women will not transition out of work and this contributes to a relatively low observed exit rate within the affected households. The opposing influence that financial need and need for care have on women’s employment may preclude any finding of statistical significance, in which case this result cannot be interpreted as evidence that partner health has no effect on older women’s chances of remaining in work.

Given the above, it is suggested that additional confounding factors pertaining to financial circumstances may determine the outcome for women’s employment in the advent of poor partner health. Blau and Riphahn (1999) analyse spousal health and it’s effect on couple’s retirement patterns in Germany, and find that the influence of male partner health on women’s transitions is contingent on his labour market position. Results of this thesis confirm that male partner’s employment status has a direct effect on the timing and nature of the female partner transitions, but as no main effect of male partner health was found an interaction term is not considered. Analysis of employment transitions from a sample of couples selected on health status would facilitate a more detailed examination of the effect of spousal health; any such analysis would need to involve more comprehensive range of income and household financial factors than those considered in this thesis.

7.3.2.2 Pension wealth

This research provides clear evidence of the asymmetric impact that household pension wealth has on the employment trajectories of older women and their partners. Pension wealth does not influence the age of women’s exit from employment prior to eligibility for the state pension, but it does determine the timing of transitions for their male spouses. This find-
ing is commensurate with that of Loretto and Vickerstaff (2013) and Duberley et al. (2014). Their qualitative evidence suggests that knowledge and understanding of pension provision is often the responsibility of the male partner in coupled households, with the female member having minimal involvement. Existing international quantitative retirement studies show evidence of an asymmetric pension effect amongst German couples (Drobnić, 2002), whilst Szinovacz and Deviney (2000) analyse American data and conclude that both spouses adjust their retirement timing.

The disparity between the European and American findings is a possible consequence of differences in the measurement of pension assets, and the degree to which indicators capture gender imbalance in pension rights. Private and occupational pension wealth in the UK tends to be concentrated amongst employees with full time and continuous employment records. Men are more likely be in this position than women, and consequently contribute a greater proportion of the household pension fund. Gender inequity in pension resources is observed across Europe (Frericks et al., 2007), and Banks, Emmerson, Oldfield and Tetlow (2005) find that between 60 and 70 percent of a couple’s combined state and private pension resources are typically held by the male partner with 30 to 40 percent attributed to the female member. This asymmetry is reflected in the differential impact of pension wealth on the retirement patterns of the male, but not female, partners in this thesis as well as in Drobnić’s (2002) German study. In the American domain, gender inequity in pension rights is recognised (Jefferson, 2009), but pension resources are found to impact on both women’s and men’s retirement patterns (Szinovacz and Deviney, 2000). Szinovacz and Deviney (2000), however, use an indicator for receipt of individual pension income in their study, whereas Drobnić (2002) examine individual measures of eligibility and coverage of pension plans, and a household wealth quintile measure is used in this thesis. A binary indicator of whether pension income is received or not may not capture gender inequity in pension resources to the same extent as measures of coverage or wealth.

The advantage of using a pension wealth measure in this thesis, with respondents categorised into quintile groups, is that it allows for a detailed investigation of transition risk for women at different points of the wealth distribution. We can, consequently, determine likely employment patterns of persons from the middle pension wealth categories. This pop-
ulation has been termed the ‘missing middle’, because little is known about their later life employment trajectories; previous research tends to focus on those at either end of the wealth spectrum (Loretto and Vickerstaff, 2013). Our results show that the risk of exit for women prior to state pension age is the same irrespective of pension resources, but a linear relationship is established for the male partner’s risk of exit. High accumulated wealth is associated with early employment exit of the male spouse whereas low pension wealth predicts longer employment spells. Men from the poorest of households have an approximate risk of exit that is 51.9% lower than it is for male partners from the wealthiest of couples, and within the middle quintile group the probability of exit is approximately 44.8% lower than for those with the highest level of wealth. Men from the wealthiest of couples, therefore, are at higher risk of transition, whilst the poorest have the lowest risk and those from the middle pension wealth group have a level of risk that falls in between these.

Gender issues in the retirement process were discussed in the theoretical framework section of Chapter 1. The social divisions of welfare perspective of Mann (2001) was explained, in which it is claimed that women provide a disproportionate amount of informal care and domestic work. This can exclude them from occupational, private and public forms of support. The productive ageing perspective was also considered, in which Bass (2011) asserts older people should be offered opportunities to partake in meaningful activities, including paid employment, unpaid work or the provision of domestic care. Möller (2010) gives a gendered view of productive ageing, and claims women tend to move between these different forms of engagement more often than men. These views are supported here, with our empirical evidence suggesting that women’s retirement timing is influenced more by family care and partner circumstances than financial position. The effect of care is not observed on transitions of the male partners, whilst pension wealth is influential.

7.3.2.3 Partner’s employment status

Existing quantitative studies of couple’s retirement have established that working couples tend to coordinate their exit from the workforce and persons with a non-working partner are more likely to retire (Blau and Riphahn, 1999; Szinovacz and Deviney, 2000). Results from this thesis are consistent with this; however we further contribute to understanding of
women’s employment exit by differentiating between the non-working states of their partners. The cited studies are limited in scope, because retirement is the only non-working state that is analysed. In our analysis of ELSA households, rather than focusing only on those containing employed or retired men, we also study couples where the male partner is in an alternative ‘not working but not retired’ state of either illness, caring or unemployment. This provides a more detailed insight into the interaction between older women’s domestic circumstances and their employment pathways. The risk of an older woman leaving employment changes according to the male spouse’s specific position; within households comprised of a working woman and her retired partner, the female member has an estimated 57.8% higher probability of early exit compared to women in couples where both are employed. In the second type of household containing ill, unemployed or men in caring roles the risk of the female partner leaving work is approximately 18.5% higher compared to women with working spouses. This is a significant effect, but notably is lower than that for women with retired partners. These findings provide support for the first research hypothesis in that the conditional probability of older women’s exit from employment is contingent on whether her partner is employed, retired or in an alternative inactive position.

7.4 Methodological contributions to women’s retirement research

The conclusions discussed in Sections 7.2 and 7.3 illustrate the advantage of applying quantitative research methods to the study of women’s retirement in the United Kingdom. We have identified which aspects of the domestic context are statistically significant predictors of older women’s employment exit and measured the associated increase or decrease in risk of each. Previously, understanding of the interaction between women’s employment and household circumstances in the UK was informed from qualitative interviews (Loretto and Vickerstaff, 2013; Duberley et al., 2014); these studies raise health, caring, partner’s employment and financial factors as important for women’s labour market exit. The research presented in this thesis furthers understanding by quantifying the effect of influential predictors.
Quantitative analysis of women’s retirement data is seen elsewhere in international literature (Blau and Riphahn, 1999; Szinovacz and Deviney, 2000; Drobnič, 2002; Madero-Cabib et al., 2016). However we modify the approaches taken in these studies and in doing so make a number of methodological contributions to the field of women’s retirement research in the United Kingdom. The first relates to the representation of retirement as a dynamic ageing process, and the structure of the time axis along which observations are placed in the application of event history models. Decisions concerning the configuration of the time scale and inclusion of delayed entry participants can give rise to complex patterns of missing data and this has consequences for the results and conclusions of the fitted models. The second methods issue relates to the operationalization of the domestic context. These points are discussed in this section.

### 7.4.1 Conceptualizing retirement as an ageing process

In the theoretical framework presented in Chapter 1 retirement was conceptualized as a dynamic process that evolves as women age. This was reflected in our methodology with the use of discrete time event history models that have age as the chosen metric for time. A multilevel perspective was taken, with repeated observations of women’s, partner and household characteristics at the lower level and time invariant characteristics at the upper level. This framework allowed a flexible representation of the relationship between age and the probability of labour force exit, and a person’s health, income, wealth and other relevant covariates were incorporated as dynamic entities that reflect any change in status or value as people grow older. This approach, however, differs from that seen elsewhere in the literature (Szinovacz et al., 2001). Retirement in such studies is theoretically presented as a dynamic process, but age is not used as the time metric in the fitted models. Rather, a ‘time on study’ axis forms the basis of analysis.

Related literature that considers the metric for time in event history models is located in the health and epidemiology fields, but involves continuous rather than discrete time specifications (Kom et al., 1997; Lamarca et al., 1998). These papers find that final models are less complex, easier to interpret and more meaningful when age is the chosen metric. Chapter 6 of this thesis is a detailed investigation of the sensitivity of our results to the time structure
Figure 7.2: Risk trajectories for significant predictors of women’s labour market exit

used; the discrete time models fitted for the prediction of women’s transitions using an age axis were estimated a second time using a re-configured time on study metric. From this we draw similar conclusions to those just given in that, in this retirement context at least, results have more substantive relevance under the age configuration. With an age axis model risk profiles of employment exit are relatively straightforward to construct for women with different individual characteristics and household circumstances. The significant predictors of women’s transitions can be ranked in order of the influence they have on the probability of exit as women grow older.

Figure 7.2 illustrates the advantages of modelling retirement under an ageing framework. This graph, which was first presented in Chapter 3, plots the predicted probability of exit at each year of age for a woman with each given attribute, when all other covariates are held at median or modal values. Women with caring duties, poor health or a non-working partner have the highest conditional probability of exit, whilst renting or an outstanding mortgage is associated with lower risk and longer working lives. Additionally, there is minimal difference in the estimated transition probability of significant predictors for women at the younger end of the studied age range, but by age 59 those with caring duties, poor health or a non-working partner have a considerably higher predicted conditional probability of leaving work.

The sensitivity analysis presented in Chapter 6 shows that, with the exception of the indicator for male partner’s employment status, parameter estimates from each of the age
and time on study event history specifications are similar in magnitude, albeit with larger standard errors and uncertainty. However in the age scale model the labour market position of the male spouse is statistically significant at the 5% level, but it is not if the time on study metric is used. When women’s employment, health and financial trajectories are positioned within an ageing framework those partnered to non working men are found to have a higher risk of leaving work than women with employed partners, but this effect is not found when observations are sequenced according to how long respondents participate in the ELSA study. Using an age metric is important for the study of male partner’s employment as their work status determines the combined income of the couple as well as their potential joint leisure time as the female partner approaches state pension age. In a time on study specification this context is lost.

Fitting event history models using an age axis and ELSA data involves the complex rearrangement of respondents’ employment, health, financial and other covariate data. This can result in missing data problems due to the projection of biennial data onto a single year age axis. The time on study approach has the advantage that, compared to using an age metric, data preparation is more straightforward and missing data issues are minimised. Results from this method are, however, more difficult to interpret. The construction of trajectories depicting the retirement process, such as those shown in Figure 7.2, would involve merging results from multiple fitted models if a time on study specification was used. Using an age axis, in contrast, requires more difficult rearrangement of observations at the data preparation phase, but affords more meaningful and informative interpretation of parameter estimates. Trajectories that show how the retirement process unfolds as women age are straightforward to identify and construct using this approach.

The aim of the sensitivity analysis summarized here was not to produce a formal argument of the impact on parameter estimates of different time specifications. Rather, it was to advocate for the harmonisation of the modelling approach with the theoretical conceptualization of the process in question. In our theoretical framework we depicted retirement as a dynamic ageing process and modelled it as such. Whilst this did result in a more complex and involved analysis we have been able to achieve a more comprehensive understanding and representation of women’s transitions out of the labour force.
7.4.2 The operationalization of the domestic context

A difference between the methods used in this research and elsewhere is in the operationalization of the domestic context, and the way in which the household and employment domains are represented and incorporated into the modelling process. One approach for analysing couple’s employment trajectories is for the selected sample to include both male and female partners, with all observed transitions from both members pooled together and jointly modelled; Szinovacz et al. (2001) is one example of this. In such models, a gender covariate accounts for any difference in risk between couple members, and evaluating the relationship between the domestic context and women’s employment involves estimating interaction terms between the gender and household indicators. There is, however, a limit to the number of these terms that can be assessed.

To obtain the detailed insight into older women’s employment patterns that the research questions of this thesis require we have adopted an alternative analytic approach from that just described. The transitions of older women are modelled separately from those of their partners and consequently, dependency between an older woman’s employment domain and her domestic context is directly established without the need for complex interaction terms. Because of this we are able to determine whether the influence of the household and partner measures of interest differ for varying subgroups of women. In our analysis the relevant household measures are configured as categorical indicators, which allows us to quantify the impact of family measures on employment for women from different pension and non pension wealth quintiles, for women partnered to men with different levels of labour market engagement and for women with partners in varying health circumstances. Subsequently we gain a more comprehensive understanding of the relationship between the domestic context and women’s retirement than what could be achieved from modelling couple’s transitions jointly.

Blau and Riphahn (1999) take a different approach to the joint modelling of couple’s employment transitions. Rather than pooling men’s and women’s data they examine transitions using, as their unit of analysis, the employment status of each pair in their sample rather than of each individual member. This method involves modelling couple’s changing circumstances between either both being employed, both not employed, only the male mem-
ber working, or only the female partner working. Individual level indicators for each partner and combined measures of financial variables are incorporated as predictors. In this specification, therefore, the relationship between the domestic context and women’s retirement is measured via the impact of spousal and household attributes on the observed change in the couple’s status. As a result asymmetric effects are identified, but, as a disadvantage, because of sample size limitations each respondent can only adopt an employed or non-employed state. This approach precludes a more detailed consideration of different types of employment such as part time working patterns and the analysis of transitions in to and out of the various forms of non-employment, including retirement, long term illness, unemployment or caring. If this method was applied to our ELSA sample we would gain no insight into how employment trajectories might differ for women with alternative working hours, or whether personal, partner or household attributes have a differential impact across different exit pathways; information that was necessary to address the second research question of this thesis.

By analysing women’s transitions separately and fitting a conditional logit model, sample size issues were overcome and we were able to complete the detailed analysis required for the second hypotheses. Results from this process are discussed in depth in Section 7.5 below.

The detailed findings that arise from analysing men’s and women’s samples separately in this thesis, and operationalizing the domestic context in the way described above, illustrate the relevance of life course theory for studies of women’s retirement. Life course theory, as first explained in the theoretical perspectives presented in Chapter 1, provides a formal structure for conducting a comprehensive and detailed investigation of men’s and women’s retirement patterns in the household setting. The ‘linked lives’ principle encapsulates dependencies between partners, children and family members, and our empirical results show there is a significant relationship between male spousal characteristics and family caring needs and the timing of older women’s employment transitions. The ‘contextual embeddedness’ component of life course theory allows for heterogeneity in household circumstances. Findings indicate the likelihood of a woman experiencing a voluntary transition prior to state pension age differs according to the amount of pension wealth accumulated by herself and her partner. Our empirical results, therefore, reflect principles of the life course approach and illustrate the importance of accounting for spousal interactions and the domestic context.
in any theoretical representation of retirement. The identification of partner and household sources of heterogeneity in retirement patterns stems from the operationalization of the domestic context, and afford a detailed representation of women’s retirement.

### 7.5 Determinants of voluntary and involuntary pathways

Sections 7.3 and 7.4 discuss the influential predictors of older women’s labour market exit and the advantages of the methodological approach used to conduct that part of the analysis. Here the focus is on the factors that influence the nature of any transition that occurs and whether it is the involuntary or voluntary pathway that is subsequently followed. As we explained earlier in the overview of Section 7.2 and summarize again here, 9.8% of the sampled ELSA women took an involuntary route out of the labour market with exit most likely to occur at ages 54/55. Women on this pathway reported a position of caring, illness or unemployment after their transition and typically did not report as retired until the state pension age of 60. The voluntary exit pathway is characterised by women who report as retired immediately after exit. Their most probable age of exit is later, at 56/57, and 8.5% of women followed this route. The rate of return to work across the two pathways is low; the majority tend to stay in non working states, with 2.5% of the 1569 sampled women having a recorded return to work. The second research question of this thesis relates to the factors that determine which of these two pathways is most likely to be taken. Our hypotheses state that poor health of a woman or her partner predicts involuntary exit, whilst voluntary transitions are associated with household pension wealth. We find no evidence that poor health influences women’s retirement pathways, despite having established it as a determinant of the age of withdrawal from the labour force. Partner’s employment status, along with accumulated household pension wealth and personal income, are found to be the most influential predictors of the voluntary and involuntary trajectories. In the following sections these results are discussed in more detail with reference to relevant literature surrounding women’s and couple’s retirement patterns.
7.5.1 The influence of partners and pensions

A particular point of note from the findings summarized above is that, whilst health status predicts the age at which women are likely to leave the workforce, it does not determine whether it is the voluntary or involuntary pathway to retirement that is followed. This is contrary to expectations in that it was hypothesised that women who leave work due to poor health would experience an involuntary exit and report a labour market position that corresponds with this. This is not the case, however; our results indicate that women with poor health are as likely to report their labour market status as retired as they are to report having an involuntary exit. The same, incidentally, is found for women with caring responsibilities. Caring obligations predict shorter working lives, but do not necessarily mean that women subsequently follow the involuntary pathway to retirement. Carers are equally likely to report their labour market status as either retired or looking after home and family. These results highlight the confusion surrounding whether and when women consider themselves retired as opposed to being in any other inactive labour market position. This debate is raised in women’s retirement literature (Loretto and Vickerstaff, 2013; Duberley et al., 2014) and our contribution to it is presented in Section 7.5.2 below.

Results in this thesis show the hypothesised significant relationship between pension wealth and the probability of voluntary or involuntary transition into retirement. Women in the wealthiest of couples are most likely to experience a voluntary transition and report as retired immediately after their exit. However women in the middle pension wealth groups, who have been identified as particularly under researched (Loretto and Vickerstaff, 2013), have odds of involuntary exit that are approximately twice as high as their wealthier counterparts. Women from the poorest households are five times more likely to follow the involuntary pathway compared to those in the wealthiest quintile. After their transition, they tend to report as having poor health, caring duties or as unemployed and typically report as retired only upon reaching state pension age.

These findings are analogous with those for older men, as explained by Banks and Smith (2006). From their analysis of retirement patterns for males from different wealth quintile groups, these authors establish that those from the upper end of the wealth distribution who leave work prior to state pension age tend to identify as retired. Men with the lowest lev-
els of wealth, who are not working, but also not yet of pensionable age, typically report an alternative non-working inactive state. The labour market position of the male partner in our sampled households was found to be a significant predictor of whether women take the voluntary or involuntary pathway out of work; it is unique amongst the studied covariates in that it determines both the timing and nature of women’s employment transitions. Women partnered to retired men are themselves more likely to report as retired whereas those with spouses in alternative not working, but not retired states are at greater risk of following the involuntary labour market exit route. Evidence for correlated labour market positions within couples are is found elsewhere using German and Spanish data (Blau and Riphahn, 1999; Radl and Himmelreicher, 2014). These studies show that the labour market withdrawal of one spouse is accelerated if the other is not employed. Our analysis focuses on the effect that the male partner’s employment has on the female member, and we have established that, in the UK context, women’s labour market exit is precipitated by that of her spouse. Additionally, the pathway that she follows to retirement after any transition is likely to correlate with that of her partner.

Taken together, our results and those from existing literature point to two distinct household types differentiated by wealth. The most affluent couples are likely comprised of a retired man, and female partner who follows the voluntary route out of work and also reports as retired. In the least wealthy couples, the male partner is also out of work, but reports an alternative inactive position. The female member in this case is at higher risk of taking the involuntary pathway and reporting as either ill, in a caring role or unemployed. Note, however, that whilst pension wealth predicts the age at which the male partner is likely to leave the workforce it does not directly determine when the female partner is likely to do so. Rather, our results show that it is the male’s own employment status that determines this. What this is suggestive of, then, is an order in which pension wealth determines the labour market exit of the male partner and then his subsequent position determines the timing and pathway of his wife’s exit.

The relationship between a couple’s pension wealth and the employment transitions of each couple member is indicated in Figure 7.1 on page 243. The probability of the male partner transitioning from employment is responsive to the level of pension wealth accrued
by the couple, and the female partner’s employment exit is in turn influenced by the resulting non working status of the male partner. Previously, the interaction between pension wealth and women’s retirement in the United Kingdom had not been formally modelled; in this thesis, we have shown that the effect operates indirectly through the influence of the male spouse. These results show an enduring influence of the patriarchal ethos, which states that the balance of power in retirement negotiations between spouses is held by the person with the most valuable resources. This hypothesis was first raised in the discussion of theoretical retirement perspectives in Chapter 1. An alternative explanation, of female dominance, gives the greatest influence to the person with the most valuable social assets. Results suggest that retirement timing within couples may be driven by financial resources, but the balance of household pension wealth tends to be held by the male partners. This influences the timing of their employment transition, and the female spouse then adjusts her labour market position to follow that of her partner. This is reflective of a patriarchal ideology, with the male spouse having the greatest influence in the retirement decision.

7.5.2 The beginning of retirement for women

With the results explained in this chapter we can consider methods for identifying the entry point into retirement and contribute to the current debate surrounding women’s confusion and uncertainty about whether and when one becomes ‘retired’. Existing research into women’s later life employment patterns emphasise the limitation of traditional models, which depict retirement as an abrupt ending to continuous full time employment (Loretto and Vickerstaff, 2013; Duberley et al., 2014). Whilst this thesis does not have an explicit research question or hypothesis focusing on this issue, it is an important one for the developing field of older women’s employment research in the United Kingdom and thus deserves some attention here.

Analysis presented in this thesis confirms that a transition from the workforce does not determine the beginning of retirement for all women. Of the 287 women with an observed transition in the studied ELSA sample, 27% continued to work part time and 25% had recently provided care for someone in need. In such cases women may not consider the ending of full time paid employment as signifying retirement, because work for them, whether paid
or not, continues. The concept of retirement for women is associated with financial resources and the employment status of the male partner. The poorer respondents that were studied, as well as those coupled to men out of work and unemployed, ill or in a caring role, did leave the labour force prior to the state pension age of 60, but did not report as being retired immediately after their transition. Rather, they tended to do so at 60. Women from high pension wealth households or with a retired spouse did identify as being retired directly after exit, but before being eligible for the state pension at 60. These findings provide empirical support to existing literature that claims retirement is not necessarily synonymous with leaving employment.

Banks and Smith (2006) provide two alternative events that signify the transition point between not being retired and being retired, rather than the complete and final withdrawal from the labour force. The first of these is self perception of labour market position. The outcome measure used in the analysis of this thesis is based on self described employment status and as such, informs with regards to when women are or are not likely to perceive themselves as being retired. Our results show that the likelihood of doing so is not equal for all women and is dependent on financial circumstances and partner’s labour market position. Consequently, should this measure be used to identify and select retired women then the resulting sample would likely include those who left work younger than state pension age and are from a wealthy and high income household or have a retired spouse. Poorer women of this age group, and those with non-working, but not retired partners, would be excluded. Relying only on a self reported employment status for identifying retired women is likely to lead to a biased selected sample.

An alternative means for detecting the onset of retirement given by Banks and Smith (2006) is the receipt of state or private pension income. Our results show that poorer women tend to report as retired at the age of eligibility for the state pension, whilst wealthier women do so earlier, typically close to the time of their transition out of work. Women in this sample have not yet reached state pension age; but there is a marked difference in the proportion of sampled couples from each pension wealth quintile group that were in receipt of private pension payments at the time of the woman’s transition out of work. Of the women with an observed transition, only six percent that were in the poorest quintile received private pension
benefits compared to 31% of couples from the middle quintile and 32% in the wealthiest. Rather than private pension payments the poorest of couples are more reliant on state benefit support; 42% of the least affluent women were reliant on this form of income compared to 29% from the middle and 13% of those in the highest pension wealth quintile. These figures suggest that wealthier women, who are more likely to report as retired prior to state pension age, are also more likely be in receipt of private pension payments than those with the lowest levels of pension wealth. Older women may not, as this discussion confirms, identify with the traditional concept of retirement as the ending of employment; rather they are referencing their partners and spouses, and the receiving of pension payments.

7.6 Policy implications

In this section we consider how the results of this thesis relate to recent changes to the pension system in the UK. Women’s state pension age is legislated to rise in stages from 60 to 65 by November 2018, after which the age of entitlement for both men and women will increase to 66 by October 2020 and 68 by 2046. Additionally, a single tier pension has been introduced for persons who reach state pension age after 6 April 2016. This replaces a previous two tier system comprised of a basic amount with second tier supplementary pension. Cribb et al. (2013) examine the impact of the first incremental rise in women’s state pension age from 60 to 61. They find that employment rates for 60 year old women increased by 7.3 percentage points, whilst employment rates of their male partners rose by 4.2 percentage points. The proportion of unemployed 60 year old females also increased, by 1.3 percentage points. Cribb et al. (2013) conclude that this pension age reform has a significant effect on labour market participation of older women. The single tier reform is expected to be advantageous for women in the short term, with 61% of those retiring between April 2016 and April 2020 set to receive a higher pension income under this system compared to the previous (Crawford et al., 2013). Of interest here is how the raising of the age of entitlement and single tier pension reform may together impact on the timing of transitions from the labour market of women aged between 50 and 59.

Evidence produced in this thesis shows that women aged between 50 and 59 do not adjust the timing of their labour market exit in response to pension wealth. Rather, exit is
predicted by having a non-working spouse, caring obligations and own poor health with an estimated 18.3% of employed women aged 50 to 59 transitioning for these reasons. Given that an individual’s pension wealth is a function of both the age of entitlement and the amount received, it follows that raising the state pension age for women, or changing the value of their pension income, may not result in a corresponding increase in the length of time they spend in work. Adjusting the age of entitlement and amount paid might change lifetime pension wealth, but there is no evidence that this will influence the age at which older women leave the labour force.

Under the pension age and structure reforms, women who leave the labour market prior to the age of eligibility, for reasons related to partner’s employment, caring obligations or health, may instead face a longer period of time in which they are not employed, but also not in receipt of any personal state pension income. Figure 7.3 on page 263 illustrates. This is an adaptation of Figure 7.1 presented earlier in this chapter and shows women’s predicted exit pathways given an increase in their pension age from 60 to 65. Our research found that 9.8% of working women aged between 50 and 59 followed an involuntary pathway characterized by time spent in poor health, fulfilling caring needs or in unemployment. The typical age of exit for women on this pathway is 54/55. The most common age of women who transition through the voluntary early reported retirement pathway is 56/57 with an estimated 8.5% of working women aged 50 - 59 taking this route. An average woman on the involuntary pathway with a state pension age of 60 could experience a wait of five to six years before receiving pension income, with a typical woman on the voluntary route having a three or four year delay. A state pension age of 65 or later could add five years or more to the length of time between leaving work and receiving the state pension.

Support for women between transitioning out of work and receiving state pension payments may come from alternative public welfare schemes, if they substitute disability or unemployment insurance for lost pension income. Disability insurance criteria are less stringent than those for unemployment and recent evidence shows that the proportion of older women claiming the disability benefit is rising (Kemp and Davidson, 2009). This trend may continue at an accelerated rate with the forthcoming increases in women’s state pension age. Alternatively, should disability criteria be tightened, then a rise in unemployment benefit
Figure 7.3: Older women’s pathways to retirement with increase in state pension age.
claims could be expected if this becomes the state pension income substitute.

The dependency of older women’s employment transitions on partner’s employment, as established in this thesis, may mean that the proposed increase in men’s state pension age has an effect on women’s exit rates. Results show that the timing of male partner transitions out of work is influenced by pension wealth and, additionally, their labour market position determines the timing of their wives’ transitions. It then follows that if working men react to the raising of their pension age by remaining in employment for longer we could expect an associated effect in the labour market retention of older women, with the length of their employment spells also increased. Alternatively, men’s increase in state pension age could lead to a higher rate of disability claims as described for women above. If the rise in men’s state pension age motivates the substitution of disability benefits for pension income, rather than longer employment spells, then there may be a flow-on effect and a rise in claims from the female partners.

In conclusion, the impact of recent pension reforms for women may have limited direct influence on their retention in the workforce between the ages of 50 and 59. Responsibility for caring, partner’s employment and their own poor health are the predominant reasons why older women leave work and these influences persist irrespective of the age of eligibility and value of their pension wealth. Rather, the impact of pension reform may be to lengthen the period of time between any transition from work and receipt of pension income. This could lead to a substitution effect and increase in women’s disability or unemployment benefit claims. An indirect impact on women’s employment exit may be observed due to the relationship between their likelihood of transition and the male partner’s labour market position. Male spouse’s transitions are responsive to pension wealth and thus any change to their state pension assets may have a consequential impact on female partner’s likelihood of employment exit.
7.7 Assumptions, limitations and recommendations for further research

A summary of assumptions applied to the modelling process is presented in the next section, with limitations and recommendations for future research discussed following that.

7.7.1 Assumptions applied to the modelling process

The conclusions drawn from this analysis are subject to a number of assumptions. The first concerns the use of the complementary log log (cloglog) link function, rather than a logit link, in the event history models for women’s and male partner transitions. The cloglog option was chosen, because although employment transitions take place in continuous time, information on these transitions has been collected in discrete intervals. In such instances the cloglog link is recommended as it invokes a proportional hazard assumption analogous to continuous time hazard models (Singer and Willett, 2003). Under this assumption, the hazard for any individual is assumed to be a fixed proportion of the hazard for any other subject, with each predictor having a constant multiplicative effect.

The event history models presented in Chapter 3 were fitted under a conditional likelihood framework, in which it was assumed that the first transition observed is the first that occurred. This approach facilitates the inclusion of left truncated data, and results from the fitted models give the probability of an employment transition at a given age conditional on no prior transition occurring since the age of 50. There may be respondents in the analysed ELSA sample for whom this does not hold; these women have earlier transitions that are not observed, because they occur between the age of 50 and their entry into ELSA. If the probability of leaving a job at a given age is dependent upon the number of previous transitions made, then the fitted models presented in this thesis may underestimate the risk of transition for women with prior unobserved job changes.

A third assumption applied to the use of event history models in this research concerns the use of right censored data. Right censored cases are included in the selected ELSA sample, and arise from the ending of individual observation periods before any employment transition occurs. In such cases it is assumed that censoring is non informative, in that
the censoring mechanism is unrelated to and independent from the cause of any impending employment transition. Allison (2010) asserts that violation of this assumption can lead to biased parameter estimates, but also that there is no available method to test for it and limited options for correcting any bias that may arise should the assumption not hold.

7.7.2 Limitations and recommendations for future research

The analysis in this thesis focused exclusively on coupled working women aged between 50 and 59, rather than the wider population of both partnered and single working women of this age. The restriction on household composition was justified in Section 1.7 with a comparison of the financial resources of coupled and single older women, and discussion of differences in caring demands, health effects and leisure opportunities that may arise from the presence of a partner in the household. Variation in domestic circumstances within the single older women population was also considered, including that attributable to marital and relationship history. These differences preclude the simultaneous modelling of coupled and single women retirement trajectories, and the set research questions focused on the interaction between coupled women’s domestic circumstances and their retirement pathways.

Restricting the analysed sample to only partnered women means that findings cannot be inferred to single women of the same age. The nature of the conclusions drawn, however, suggest that the decision to restrict the sample to couples was an informed one; partner’s employment status is established as influential for determining both the timing and nature of coupled women’s employment trajectories, with the female spouse tending to adopt the same labour market status as her partner. Including single women in the same sample as coupled, and simply adjusting for marital status by including a relationship covariate, may not capture this influence.

Analysis of the effect of pension wealth on employment exit may also have been problematic if single and coupled women’s data was pooled. Due to the lack of any partner contribution, women living alone tend to have considerably less pension resources than their coupled counterparts, and would most likely be positioned at the lower end of a joint pension wealth distribution. Adjusting any pension wealth variable to account for difference in household size and composition would be analytically challenging. In light of these limi-
tations, a comprehensive, separate analysis of single older women’s employment pathways is recommended as an area for future research. This should examine the effects of financial circumstances, family composition and proximal and earlier life course events on retirement patterns, and compare trajectories for those divorced, widowed or never married.

A further limitation of the analysis conducted in this thesis arises from the exclusion of job quality variables in the fitted models. Job satisfaction, security and adequate pay and training were raised in the literature review of Chapter 1 as being influential for women’s labour market participation. However after scrutiny of response rates and observation patterns for these measures it was not feasible to incorporate them in the modelling process. As detailed in Chapter 2, job related questions were not asked in the first wave of ELSA and in waves 2 to 5 were part of the self completion module that has lower response rates than the core ELSA questionnaire. Consequently observations of job quality measures have a higher rate of missingness than other studied covariates with imputation of unknown values not viable, because of related missingness in other questionnaire items. A random effect was included in the final fitted model for women’s transitions to account for time invariant unobserved heterogeneity; this is an appropriate correction if it is assumed that job quality is a fixed measure. Arguably, however, job satisfaction and related issues are dynamic constructs that change over time. Our recommendation, therefore, is that subsequent research into the effect of job quality on older women’s work transitions considers these factors as time varying, and analysis be conducted over a different time frame using fewer or alternative ELSA waves to the five analysed for this thesis.

A final recommendation for future research into later life employment trajectories concerns the effect of poor partner health on women’s retirement patterns. No evidence for a statistically significant result was found in our work, but this is the possible outcome of two opposing mechanisms that may mask important and significant relationships. In the advent of poor partner health an older woman may either leave work to provide care or, alternatively, remain in employment to replace lost household income. Women’s transitions in these circumstances may be contingent on the couple’s income or other financial circumstances. Investigating this further requires analysis of a wider range of financial measures than those included in this thesis and it is therefore a suggested topic for future women’s
7.8 Conclusion

This thesis began by citing a recent government report that details the challenges associated with an ageing population in the United Kingdom (House of Lords, 2013). Public welfare expenditure may be strained as the proportion of retirees and inactive older persons in the population increases, and state funded financial support may be inadequate for sustaining a good standard of living. The retention of older persons in the workforce has, consequently, become a key policy concern. The aim of this thesis was to determine the statistically significant predictors of transitions out of employment for women aged between 50 and 59. Previously, understanding of women’s retirement patterns was informed from small scale qualitative studies with available quantitative research concentrated on men’s trajectories. The available women’s retirement literature emphasise the importance of the domestic context and gender differences in pension accrual and entitlement, but the relationships between partner and family characteristics, and pension wealth and women’s employment transitions had not been formally tested in the UK context.

For this research, a series of discrete time event history models were fitted to five waves of data from the English Longitudinal Study of Ageing collected between 2001 and 2011. The employment trajectories of women were modelled in a multilevel framework, with retirement characterized as an ageing process and health and financial circumstances incorporated as dynamic entities that change over time. Results show that the most influential predictors of women’s labour market exit prior to state pension age are own poor health, caring obligations and having a retired or inactive spouse. Transitions of the male partners, however, are predicted by household pension wealth with high levels of accrued pension resources associated with earlier employment exit. The effect of joint pension wealth on women’s working patterns is not on the age of exit, but in the pathway taken to retirement following any employment exit that does occur. Women from households with low pension resources have increased odds of experiencing an involuntary transition rather than voluntary retirement reported prior to state pension age.

The dependency of older women’s transitions on both individual and household char-
acteristics signify an enduring effect of the patriarchal ethos. Male partner dominance in decision making and retirement timing was pervasive in traditional ‘male bread winner’ households prior to the expansion of women’s involvement in the workforce. However the cohort of women studied in this thesis is associated with increased participation in the labour market, and the analysed ELSA sample contains only couples where the female member is in employment. Despite this, evidence is found of gender divisions in the retirement process. Labour market transitions of the male partner are responsive to household pension resources which implies his responsibility for the long term financial well being of the family. Women’s transitions are determined by family care and the partner’s employment status, thus showing that retirement decisions continue to be structured along gender lines. Policy aimed at retaining older women in the workforce, therefore, should account for the impact of caring and spousal factors on the timing and nature of women’s retirement pathways.
References


**URL:** [http://www.ifs.org.uk/publications/5643](http://www.ifs.org.uk/publications/5643)


**URL:** [http://www ifs org.uk comms r82 pdf](http://www.ifs.org.uk/comms/r82.pdf)


**URL:** [http://www ifs org.uk comms r73 pdf](http://www.ifs.org.uk/comms/r73.pdf)


**URL:** [http://www ifs org.uk wps wp1303 pdf](http://www.ifs.org.uk/wps/wp1303.pdf)


URL: http://ec.europa.eu/eurostat/data/database

URL: http://ec.europa.eu/eurostat/statisticsexplained/index.php/Healthy_life_years_statistics#Main_tables


**URL**: [https://discover.ukdataservice.ac.uk/catalogue/?sn=5050](https://discover.ukdataservice.ac.uk/catalogue/?sn=5050)


URL: http://hertsequality.org/downloads/content/Flexible%20Working%20for%20Older%20Workers.pdf


URL: http://dx.doi.org/10.5255/UKDA-SN-5050-11


URL: http://www.oecd.org/els/social/pensions/PAG


URL: http://www.ons.gov.uk/ons/rel/pensions/pension-trends/chapter-12–household-pension-resources/index.html


URL: http://www.ons.gov.uk/ons/rel/pensions/pension-trends/chapter-12–household-pension-resources/index.html


**URL**: https://www.keele.ac.uk/csg/downloads/researchreports/Extending%20working%20life.pdf


**URL**: http://www.ifs.org.uk/elsa/report08/elsa_w3_tech.pdf

URL: http://www.ifs.org.uk/elsa/report06/w2_tech.pdf


**URL:** [http://www.stefvanbuuren.nl/publications/mice%20v1.0%20manual%20tno00038%202000.pdf](http://www.stefvanbuuren.nl/publications/mice%20v1.0%20manual%20tno00038%202000.pdf)

